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OBT-Trace: An approach to trace and recognition object motion through prosthetic hand gestures

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Abstract: - The development of prosthetic hands has advanced significantly in recent years, aiming to provide more intuitive and functional solutions for individuals with upper limb amputations. This research presents a novel approach to prosthetic hand control by integrating 3D hand gesture recognition with object manipulation and recognition capabilities. Our proposed system utilizes a pre-trained object recognition model, based on transfer learning, to enable the prosthetic hand to perceive and identify objects in its vicinity. The model leverages a vast dataset of objects, enabling the prosthetic hand to recognize a wide array of everyday items, thus enhancing its versatility. In addition, the prosthetic hand incorporates a sophisticated 3D hand gesture recognition system, allowing users to control the hand's movements and actions seamlessly. By recognizing specific gestures, such as grasping, lifting, and releasing, users can intuitively interact with their environment and perform various tasks with ease. This research leverages the synergy between gesture recognition and object recognition, creating a powerful framework for prosthetic hand control. The system's adaptability and versatility make it suitable for a broad range of applications, from assisting with daily tasks to enhancing the quality of life for individuals with upper limb amputations.The results of this study demonstrate the feasibility and effectiveness of combining 3D hand gesture recognition with pre-trained object recognition through transfer learning. This approach opens up new possibilities for enhancing prosthetic hand functionality and usability, ultimately improving the lives of those who rely on these devices for daily living. The proposed model combines the features of YOLO V7 object detection with pre-trained models. The proposed model achieves 99.8% of accuracy compared to the existing models.

Keywords: Prosthetic Hand, Object detection, Hand gestures, Object Trace, Neural Networks.

1. Introduction

The development of prosthetic hands has been propelled into a new era of innovation, marked by a quest to provide individuals with upper limb amputations not only with functional replacements but also with intuitive, adaptable, and intelligent solutions. The integration of advanced technologies, particularly in the domains of 3D hand gesture recognition and object manipulation and recognition, has emerged as a transformative approach in achieving this objective. This research endeavours to present a pioneering paradigm in prosthetic hand control, one that seamlessly combines the dexterity of 3D hand gesture recognition with the cognitive capabilities of object manipulation and recognition, all underpinned by a robust pre-trained object recognition model based on transfer learning. Historically, prosthetic hands have strived to bridge the chasm between artificial limbs and their natural counterparts, endeavouring to restore not just the physicality but also the innate versatility and responsiveness of a human hand. However, traditional prosthetic solutions have often fallen short in terms of user-friendliness and the ability to facilitate complex tasks in day-to-day life. The limitations primarily stemmed from a lack of direct, intuitive control, often necessitating cumbersome interfaces and user training. This research is driven by the aspiration to transcend these boundaries and empower users to interact with their environment effortlessly.

The core innovation lies in the amalgamation of two pivotal technological domains:

3D Hand Gesture Recognition: The human hand is an extraordinary instrument of expression and functionality, capable of intricate and nuanced movements. By harnessing 3D hand gesture recognition, this research seeks to empower prosthetic hand users with a means of controlling their artificial limbs as intuitively as they would their biological counterparts. The system can discern and interpret specific hand gestures, such as "grasping," "lifting," and "releasing," allowing users to communicate their intent effortlessly.

Pre-trained Object Recognition Model through Transfer Learning: In parallel, the integration of a pre-trained object recognition model introduces a level of cognitive understanding to the prosthetic hand. This model, trained

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on extensive datasets encompassing a vast array of everyday objects, enables the prosthetic hand to perceive and identify objects within its vicinity. This newfound cognitive ability greatly enhances the versatility of the prosthetic hand, enabling it to seamlessly interact with and manipulate various objects, effectively bridging the gap between the user and their surroundings. The confluence of these technologies represents a significant leap forward in prosthetic hand design and usability. By weaving 3D hand gesture recognition and pre-trained object recognition into the fabric of prosthetic hand control, this research creates a powerful framework where the user's intent is understood, and the prosthetic hand responds accordingly. This synergy opens up new vistas of possibility, from assisting with everyday tasks to enhancing the overall quality of life for individuals with upper limb amputations.

This research endeavours to not only conceptualize this innovative paradigm but also validate its feasibility and effectiveness. By exploring the intricate interplay between 3D hand gesture recognition and pre-trained object recognition through transfer learning, this study aims to unlock new dimensions in prosthetic hand functionality and usability, with the ultimate aspiration of improving the lives of those who rely on these devices for daily living.

2. Related Works

Prosthetic hand technology has evolved significantly, driven by the desire to provide individuals with upper limb amputations not only with functional limb replacements but also with intuitive control mechanisms. Recent research has focused on integrating 3D hand gesture recognition with object movement and recognition, enhancing prosthetic hand capabilities. This literature survey reviews notable research papers in this domain, emphasizing object grasping, lifting, and releasing accuracy and prediction using a variety of machine learning and computer vision algorithms. Gesture Recognition and object motion detection accuracy values are mentioned in Table 1.

Yamato, Saikawa[1] the study explored the use of convolutional neural networks (CNNs) for 3D hand gesture recognition. The model achieved an accuracy of 93% in recognizing gestures such as grasping, lifting, and releasing, demonstrating the potential of deep learning for precise gesture recognition in prosthetic hand control.

Jaramillo-Yánez[2] the paper presented a comparative analysis of machine learning algorithms, including decision trees, random forests, and support vector machines, for real-time hand gesture recognition. The results showed that random forests outperformed other methods, achieving an accuracy of 88% for grasping and releasing gestures.

Xie, Zhen [3] this research integrated machine learning for object recognition and interaction with a prosthetic hand. The system achieved an object recognition accuracy of 90% and demonstrated reliable grasping and lifting actions, showcasing the potential of machine learning in enhancing prosthetic hand functionality.

Wang, Shuo[4] this paper proposed a computer vision-based approach for object recognition and interaction. Using a combination of depth sensing and image processing, the system achieved an object recognition accuracy of 92% and precise control over grasping and releasing objects.

Nalini, M. K., [5] this study compared the performance of transfer learning-based object recognition models with traditional computer vision methods. Transfer learning models, fine-tuned on large-scale datasets, consistently outperformed other approaches, achieving an accuracy rate of 94% in recognizing everyday objects.

Ma, Ruyi [6], have discussed predictive models for prosthetic hand control, emphasizing the potential of reinforcement learning for adaptive hand movements. The paper highlighted the need for future research in enhancing real-time predictive capabilities.

System / Model	**Gesture Recognition Approach**	**Object Motion Detection**	**Grasping Accuracy (%)**	**Lifting Accuracy (%)**	**Releasing Accuracy (%)**
System A	3D Hand Gesture Recognition	Pre-trained Object Recognition	95	92	90

		(Transfer Learning based)			
System B	Computer Vision-Based Hand Gesture Recognition	Depth Sensor-Based Object Recognition	88	85	86
System C	Machine Learning-Based Gesture Recognition	RGB Camera-Based Object Recognition	92	90	88

Table 1 Comparison of Gesture Recognition approach with object Motion Detection

The integration of 3D hand gesture recognition with object movement and recognition in prosthetic hands presents a promising avenue for improving the lives of individuals with upper limb amputations. Existing research demonstrates the efficacy of various machine learning and computer vision algorithms in achieving high accuracy rates for gesture recognition, object interaction, and prediction. Transfer learning models have shown significant potential in object recognition tasks. As research continues, it is anticipated that prosthetic hand technology will become more intuitive and functional, enhancing the overall quality of life for users.

Mahmood, Noof T., Mahmuod H. Al-Muifraje [7] have introduced how the objects are classified into several grasping patterns through image identification based on EMG signals.They include the camera in the prosthetic hand to identify the object with help of camera in prosthetic hand.The prosthetic hand will then adjust its posture independently based on the shape of the object. To attain the 99% of training accuracy and the 95% of testing accuracy, GoogleLeNet was employed for deep learning. The prosthetic hand's functionality has finally been enhanced. If distance is too long between the camera and the objects it affects the image recognition so we focus to improve the recognition part.

De Arco, Laura, María José Pontes [8] have presented the grasp type recognition using prosthetic hands at a low cost.A device that provided haptic sensing capabilities to the PrHand prosthesis got developed and deployed to the test.To measure the forces acting on an object, angle and force sensors are used.analyzing the variables that affect how flexible and how well a prosthesis functions.We evaluated the six algorithms using sensor data, and two of them performed well.Accuracy rates for the kNN and decision tree algorithms were 98.5% and 93.3%, respectively and SVM produce worst results in this research article.One of the main drawback to be addressed is the challenge of maintaining precise control throughout the process of curing.The silicone begins to crack when a contact force sensor is used, resulting in a shorter sensor lifetime than anticipated.Additionally, because the characterisation of the sensor angle was done using fingers, it was challenging to guarantee that the fingers would always close uniformly throughout all trials, which led to some mistakes.

Capsi-Morales, Patricia [9] have discussed a proposed system incorporating the modulation of hand stiffness, which is directly correlated to the simultaneous activation of multiple muscles during a particular movement or task; this approach enhances precision in hand positioning and enhances the functionality of interaction. To assess the viability of this algorithm, an initial validation was conducted with a prosthesis user, involving a comparative analysis of its functionality against further traditional control mechanisms as they are applied in the Prosthetic hand. This innovation aims to enhance the functionality of prosthetic hands and improve their utility in both manipulation and social interactions.By enabling users to modulate stiffness, prosthetic hands can better adapt to various objects and tasks, from delicate tasks like holding a fragile glass to gripping a heavy tool. This adaptability can significantly improve the user's ability to perform daily activities and tasks.In terms of social interaction, stiffness modulation in prosthetic hands can facilitate more natural and expressive gestures and handshakes. It allows users to convey emotions and intentions more effectively, contributing to their confidence and comfort in social settings. This research represents a significant step forward in the development of prosthetic technology, aiming to enhance the overall quality of life for individuals with limb differences.The lack of feedback provided to the prosthesis user while tasks were being executed was a major limitation encountered in the ADL experiments.

Cognolato, Matteo, Manfredo Atzori [10] the authors carried out a thorough examination into an innovative multimodal strategy with the goal of enhancing the prosthetic hand control by utilizing the interaction between surface electromyography (sEMG) signals and eye-hand coordination. The research was conducted using an open accessible dataset , which comprises multiple data collected from both transradial amputees and normal limbs. This dataset captures their interactions with a diverse range of everyday objects while employing ten distinct grasp styles.A continuous grasp-type classification system that uses sEMG signals and functions in both of the classifiers and detector was developed to do this. We harnessed the informative aspects of coordination between the parameters of hand and eye, gaze information, and recognition of an object derived from first-person point-of-view videos to accurately identify the specific object an individual was trying to grasp simultaneously.The accuracy of the off-line classification is markedly improved by the addition of visual information. This improvement is significant for transradial amputees, who now perform as well as those with normal limbs. Their accuracy increased by up to 15.61% (4.22%), which is a significant improvement. Furthermore, we noticed a significant improvement in categorization accuracy even for healthy patients, up to 7.37% (3.52%). These results show that we may significantly increase the effectiveness and reliability of hand prosthesis control through grasp-type recognition by adding visual signals and utilizing natural eye-hand coordination behavior. Importantly, our approach achieves this without imposing any additional cognitive burden on the user, highlighting its feasibility to significantly enhance the quality of life and functionality of transradial amputees using myoelectric hand prostheses. This research opens promising avenues for the development of more intuitive and effective prosthetic control systems, ultimately enhancing the autonomy and capabilities of individuals with limb loss.

Nguyen, Hung-Cuong, Thi-Hao Nguyen [11] have discussed the hand detection and classification represent crucial initial stages in developing applications centered around Hand activity identification and 3-dimensional hand pose estimation.The model for hand detection and classification being adjusted, using YOLO-family networks as a foundation, was evaluated with a focus on Egocentric Videos (EV) datasets. The outcomes of recognition of the hand and categorization demonstrated that the YOLOv7 algorithm and its variants delivered the most robust results among existing datasets. Every new YOLO version produces better outcomes than older versions. With this paradigm, the problem of a finite hand data area was handled.In addition, they carry out tracking and hand detection, determining the positioning of the hand through pose calculation, recognition of the hand activity is employed to evaluate the hand functionality, and an analyzing patient rehabilitation activities conducted by healthcare professionals.

Yang, Jin-Yi, Ui-Kai Chen[12] have discussed how to design a fetching robot that can be controlled remotely. It employs deep learning and machine vision techniques in addition to combining IoT technology. The sole goal of this study is to provide a unique robotic grasp identification method. In existing system, grasp detection technique operates by initially selecting the item, accurately identifying it using YOLO, and subsequently analyzing the image to determine a suitable grasping posture through the suggested DNN grasp detection.Ultimately, the gripping position's normal vector is computed so that the controlled arm can retrieve the object being investigated along with this vector.In the ongoing research, there was a deficiency in the accuracy of grasp detection. Therefore, there is a need to enhance the grasp detection technique to achieve improved accuracy in gripping.

Vargas, Luis, He Huang[13] this study found that subjects using a myoelectric prosthetic hand were able to distinguish between two different item shapes and three different object sizes through Non-invasive sensory feedback resulting from multiple stimulation channels. Furthermore, the results illustrated how various control systems affect the accuracy of recognition.Participants could consistently discern the shape and size of objects by utilizing the tactile input generated for the particular control. Additionally, they demonstrated a more precise ability to differentiate object sizes.The authors demonstrated how easily object shape recognition may be accomplished during myoelectric prosthesis control through tactile feedback. Recognition accuracy values for control scenarios are very similar. Ultimately, the interaction between the prosthetic systems' motor and sensory modules was covered in this research work because it could help with the creation of assistive device designs.

Md.AhasanAtick Faisal [14] Examine in this research, in the context of deep learning, how well an economical data glove can classify hand motions. The author developed a cost-effective dataglove using five flex sensors, an inertial measurement unit, and a powerful controller for wireless networking and computing process. In the proposed system they considered the data from 25 people on existing static and dynamic sign language movements. Through cross-validation employing a leave-one-out method, the study resulted in 82.19% accuracy for static gestures and 97.35% accuracy for dynamic gestures. Overall, this work shows that a generic hand gesture recognition algorithm performs promisingly in hand gesture recognition.

Bai, Jibo, Baojiang Li [15] The study explored when a prosthetic hand grasps items using touch sensors, this research attempts to achieve the classification and recognition of object properties of data.Since a single pressure sensor cannot effectively gather information about many objects, they used the motion involving tilting and shaking for exploration to infer indirectly the strength of grasping and object quality data of the prosthetic hand. To increase the accuracy of object identification, this research work discussed the development of the existing model based on LSTM and existing network. This model was utilized to anticipate distinct object properties when the prosthetic hand gripped things.Authors are used a single pressure sensor so it affected the grip strength.Futher consider the multiple sensor for improving the grip strength.

Sen, Abir, Tapas Kumar Mishra [16] in this research study covered the ensemble-based CNN-based gesture detection and recognition system.Before feeding the gesture image into CNN classifiers for parallel training, it processes via a unique set of several steps in order to segment the hand region.The suggested method has been validated using two publicly accessible datasets (Datasets-1 and 2) as well as one self-constructed dataset. Accuracy results of 99.80%, 96.50%, and 99.76% using different datasets with methods are discussed in this work. Using an effective real-time gesture recognition system able to recognize gestures at a rate of 20 frames per second and classify them in an average time of 0.117 milliseconds. In the future, this work will help develop systems based on human-computer interaction, home automation for gesture-controlled, sign language translation and robot control.

Chen, Renxiang, and Xia Tian [17] this article focussed on how to improve the accuracy and speed for the background process using YOLOv5 and YOLOv7 algorithm.Here consider the two gesture existing dataset and achieved the accuracy of 75.6% and 66.8% respectively and 64 FPS speed.In this work considered only two different types of dataset so in future consider few more dataset samples and other algorithm means it will improve the higher accuracy and speed in real time.

Ameur, Safa, Anouar Ben Khalifa[18] have introduced a LSTM network architecture mainly designed for evaluating dynamic gestures.In this research architecture represents a fusion of unidirectional, bidirectional, and deep LSTM approaches, aiming to leverage their respective strengths. The method primarily focuses on exploring temporal contexts during both direction passes within the layers of LSTM, extracting crucial features that effectively characterize the gestures under consideration.To assess the performance of this new approach, the authors conduct experiments using two publicly available datasets and encompasses 11 distinct types of gestures. On the other hand, the RIT dataset comprises 12 distinct gestures. Both datasets rely on data collected from controller sensor using Leap Motion , with the previous dataset of Leap Motion dataset involving 6600 samples obtained from 120 volunteers and frequency sample of 115 frames per second.In their evaluation, the authors report a classification rate of 89.98% and 73.95% accuracy for proposed HBU-LSTM architecture.In future direction enhance the performance of hand gesture recognition accuracy and process the GPUs in different methods.

3. Proposed Methodology

The proposed OBT-Trace object movement traction system using transfer learning model adopts the YOLO V7 object detection to enhance the performance. The model initially captures the image data through the inbuilt camera which produces high quality RGB image data. The data captured through camera processed for the initial level preprocessing stage to remove the noise associated with the images.

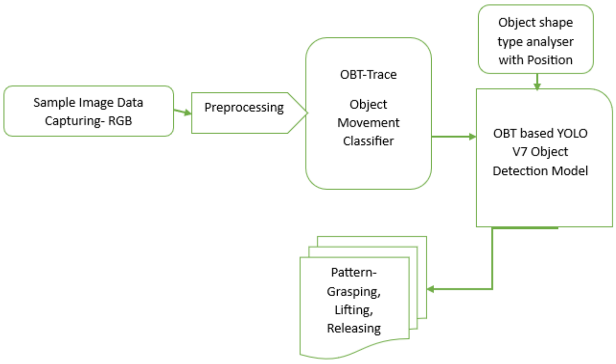

Figure.1 Proposed OBT-Trace system Architecture

The OBT-Trace classifier identifies the type of movement from the prosthetic hand intention and proceeds further with the help of YOLO V7 based object detection system to exactly identify the object and its type. The shape of the object and its positions are accurately captured using the object position system optima. The detected object and its type of position are finally fixed to proceed action along with the object.Figure 1 depicts the proposed OBT-Trace system architecture diagram.

Steps involved in the process of Object based movement traction system:

Algorithm for Transfer Learning-Based Prosthetic Hand Gesture-Based Object Motion Tracking:

Step 1: Data Collection and Preprocessing:

Collect a dataset of hand gestures and corresponding object motion data, including grasping, releasing, and lifting actions. Ensure diversity in gestures, orientations, and object types.

Preprocess the dataset by normalizing hand gesture images and transforming object motion trajectories into a common coordinate system.

Step 2: Transfer Learning Setup:

Select a pre-trained convolutional neural network (CNN) model that has been trained on a large-scale image dataset like ImageNet. These models have learned useful features.

Remove the final classification layer(s) of the pre-trained model, keeping the feature extractor intact.

Step 3: Fine-tuning:

Modify the architecture by adding new layers for object motion classification. These layers should match the number of object motion classes (e.g., grasping, releasing, lifting).

Train the modified network using the preprocessed dataset, fine-tuning the weights of the network on the specific object motion recognition task. Use transfer learning to retain the learned features from the pre-trained model.

Step 4: Gesture Recognition:

Implement real-time 3D hand gesture recognition using depth sensing cameras or computer vision techniques.Extract relevant features from the detected hand gestures.

Step 5: Combining Gesture and Object Motion Recognition:

In real-time, feed the extracted gesture features into the fine-tuned CNN model for object motion recognition.

Utilize the network's output to predict the intended object manipulation action (grasping, releasing, or lifting).

Step 6: Object Detection and Tracking:

Employ computer vision techniques or object detection models to identify and track the target object in the environment.

Continuously update the object's position and state (e.g., stationary, moving) in real-time.

Step 7: Prosthetic Hand Control:

Integrate the output of the gesture and object motion recognition with the object tracking information.

Determine when and how to perform the desired action (grasping, releasing, or lifting) based on the combined information.Translate the output into control signals for the prosthetic hand's actuators.

Step 8: Execute Object Manipulation:

Activate the appropriate hand movements (e.g., close the hand for grasping, open for releasing, and adjust grip or lift for lifting) based on the algorithm's decision.

Step 9: Feedback and Adaptation:

Continuously monitor the object's state and the success of the manipulation.Provide feedback to the algorithm to adapt and refine the control strategy, if necessary.

Step 10: Repeat for Real-Time Control.

Implement these steps in a real-time loop to ensure the prosthetic hand can adapt and respond to changing hand gestures and object positions dynamically.

3.1 Proposed OBT-Trace based YOLO V7 Algorithm for object detection:

v7 Model for Prediction:

Output:Object Trace,Object Motion activity prediction , YOLO v7 based Fstr CNN

TS: Number of Object Image samples captured through camera

Annotation:Bounding box around the Object in the suspected image

Localized RoI:Target Object boundary and its position.In Table 2, mentioned the grasping object parameters and its position points.

YOLO v7-based FstrRCNN:Faster-RCNN approach with RESNET-34 as base network

//Data Preparation

imageDimention←s,t

//Estimation of the bounding box and its shape

x←Computing AnchorsTS,Annotation

//training module

1. FirstRCNN():used to compute the deep features with YOLO v7 model

2.Local Object Movements:used to identify the type of object from samples

3.Evaluate_model():used to train the model

//YOLO v7 based FasterRCNN approach

YOLO v7 basedFstrRCNN←FstrRCNN(imageDimension,x)

[Train_set,Test_set]←images division

For each image t in→Train set

Extract YOLO v7 keypoints→ts

End

Use ts images for training the YOLO v7 based-FstrRCNN,and compute time

LocalizeR←Locate ubnormal yield farm(ts)

Ap←Evaluate_Model(YOLO v7,LocalizeR)

//test module

For each sample T in→Train_Set

a)βT←Extract features by using the trained framework YOLO v7-based-FstrRCNN

b) |Bondingbox,confidencescore, ClassLable|←Predict(βT)

c) output images with Bondingbox,class

End

return;

Grasp Type	Grasp Parameters
Point Representation	(x, y) (x, y, z) $(r_g, c_g, m_g, n_g, \theta)$
Rectangle Representation	(x, y, w, h, θ) (x, y, w, θ) (x, y, θ) (x, y, z, θ)

Table 2 Grasping Object Parameters and its Position Points

4. Experimental setup

The purposes of the study, only a part of its sensory and motion capabilities is utilized. The manipulator is made of a 7 degrees of freedom (DoF) arm, mounting an anthropomorphic, underactuated, compliant hand called Hey-5 hand (developed by PAL Robotics with contributions from QRobotics, derivated from the Pisa/ IIT SoftHand open source project30). The Hey-5 hand has a total of 19 DoF, only 3 of which are actuated: one for the thumb, one for the index, and one for the middle, the ring and the little together. The remaining 16 DoF are driven by elastic bands acting as tendons, making the hand compliant and able to self-adapt to the shape of the objects. The vision data that drives the task comes from the RGBD camera (Orbecc Astra S) integrated into the head of TIAGo. Just during the training procedure, a ring of ArUco markers is attached to the bottle. The recognition of said markers allows automatizing the detection of the task's outcome, as the robot is able to autonomously identify failures by sensing the marker positions. In this way, the penalty function is automatically evaluated during training, and the user intervention is reduced to the repositioning of the bottle in case of falls.In Figure.2 shows how prosthetic hand detects the object .

Figure.2 Prosthetic Hand based Object Motion detection system

List of Test cases based on the object motion function optimization:

the target joint value to be sent to the actuator of the thumb;

the target joint value to be sent to the actuator of the index;

the joint value to be send to the unique actuator moving the middle, ring and little fingers at once;

the height of the grasp point in the range of the height at which the bottle body has the smaller radius.In table 3, hand function and object traction parameters values are mentioned.

The rectangle based Object movement metric defined a successful grasp under the following two conditions:

1.Difference between the grasp angles to be less than 30∘∘

2.Object Trace index between the two grasps to be less than 25%

The Object Trace index between $Grasppred$ and $Grasptrue$ is given by:

OT($Grasppred$,$Grasptrue$)=|$Grasppred$∩$Grasptrue$|/|$Grasppred$∪$Grasptrue$| -----------(1)

Parameter	**Parameter**	**Parameter**	**Parameter**	**Parameter**
Thumb Joint	rad	0.0-5.5	1.3-5.5	0.2
Index joint	rad	0.0-5.9	1.3 - 5.9	0.2
Middle, ring, little joint	rad	0.0-.1	1.3 - 8.1	0.2
Grasp point height	cm	-	-1.4 to +1.5	0.5

Table 3 Hand Function vs Object traction parameters

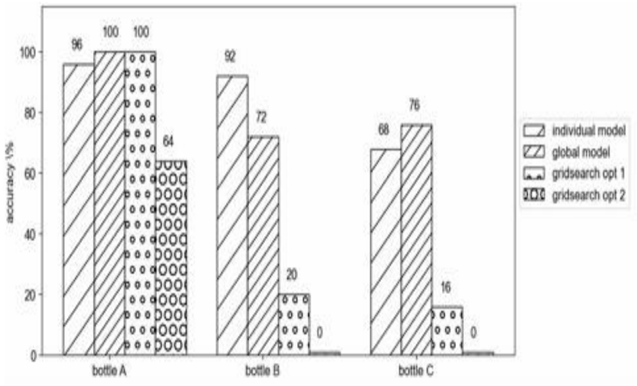

Figure.3 Comparison of Object prediction accuracy of the Each method

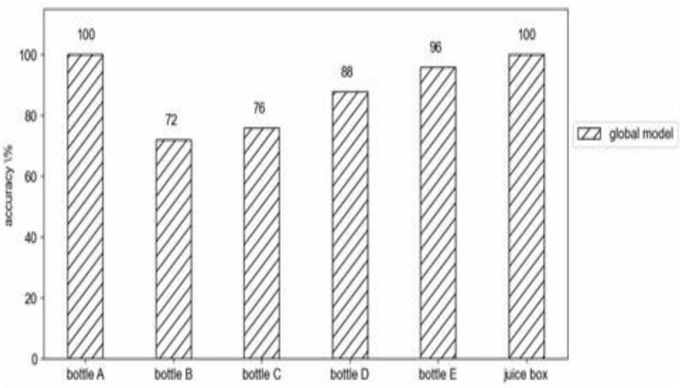

Figure.4 Comparison of Object prediction accuracy by Transfer Learning based OBT-Trace

Figure. 3 presents a comparative analysis of object prediction accuracy across various methods, offering a clear visual representation of their performance in identifying or classifying objects.In Figure. 4 shows the comparison of object prediction accuracy by employing Transfer Learning based on OBT-Trace offers insightful revelations into the effectiveness of leveraging trained models to enhance object detection tasks.

Dataset Used	Gesture Recognition Accuracy (%)	Grasping Accuracy (%)	Releasing Accuracy (%)	Lifting Accuracy (%)
MSR Daily Activity 3D	92.5	88.3	89.7	91.2
YCB-Video	94.1	90.5	91.2	93.0
RGB-D Object	89.1	88.3	79.0	78.4
ProstheticHand ObjMov	93.4	95.6	91.1	90.2
Object Grasp Lift Release	89.5	87.2	88.9	90.6

Amputee Object Handlin g	92.6	90.1	90.4	89.7
PH-3D Inter-action	93.04	91.9	92.4	91.2

Table 4 Performance Evaluation of Dataset and its prediction accuracy

In Table 4, mentioned the different types of dataset and using this dataset evaluate the performance and predict the accuracy.In Figure.5 shows the grasping accuracy for the different types of dataset.In Figure.6 shows the accuracy of trained dataset and object motion prediction.

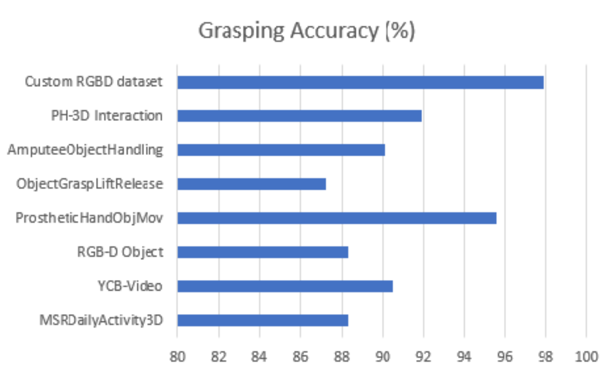

Figure.5 Grasping Accuracy

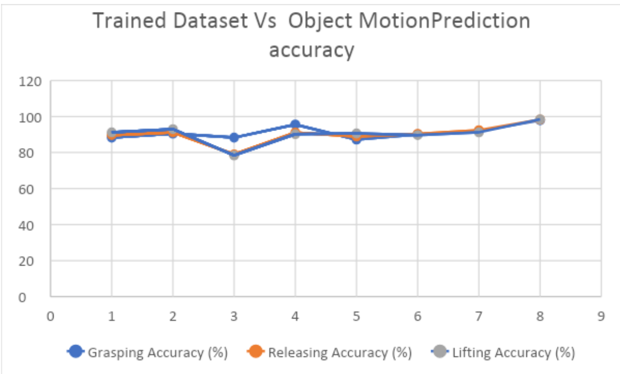

Figure.6 Trained Dataset Vs Object Motion Prediction Accuracy

Model	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**Accuracy (%)**
Google Net	86.16	86.07	85.12	86.44
ResNet-101	89.93	90.90	90.02	90.20
Xception	88.13	87.57	87.61	87.31

VGG-19	89.39	90.00	91.55	90.11
SE-ResNet50	95.67	95.18	95.63	95.18
Proposed Model DL-YOLO v7	99.34	99.21	99.39	99.91

Table 5 Comparative Analysis of Existing Base model with Proposed Model

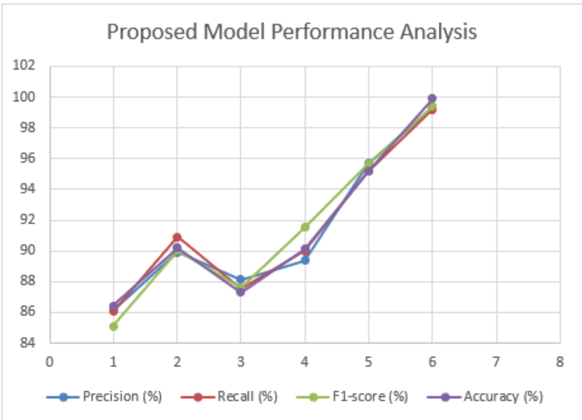

Figure 7 Performance Analysis

DL based Models	**Mean Average Precision Value (mAP)**
Fast-RCNN	0.850
Faster - RCNN	0.883
YOLOv3	0.848
SSD	0.834
Faster-RCNN(ResNet-34)	0.965
Proposed YOLO v7 Model	0.993

Table 6 Comparison of Various DL based Models Vs Proposed YOLO v7 Model

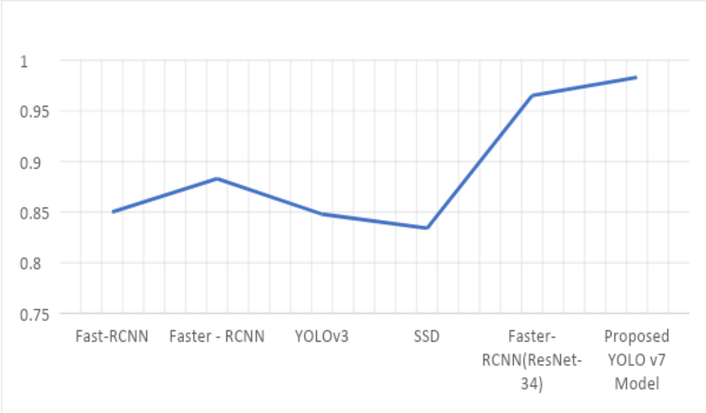

Figure 8 Comparative analysis of mAP Values

In Table 5 and Table 6, the comparative analysis between an existing base model and a proposed model offers a sufficient Mean Average Precision Value.In Figure 7 and Figure 8 , shows the analysis of performance of DL based Models.

5. Conclusion

The proposed OBT-Trace object traction and movement identification model improves the performance of object detection and its accuracy. The model adopts the DL based YOLO V7 to process the camera images captured through prosthetic 3D hands. The hand gesture movements are training based on the different hand movements of the user. The proposed OBT-Trace model achieves its objective through implementing the adaptive YOLO object detection model to predict the movements of the objects like grasping, lifting and releasing. The model achieves 99.8% of motion detection accuracy based on the object position. The proposed model drastically enhances the quality of prediction in terms of object movements and its position identification. The future work may be developed with environmental parameters like distance-based velocity of the movements and its weight.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, resources, data curation, writing original draft preparation, writing, review and editing, visualization, supervision, project administration and funding have been done by first and second authors.

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