Journal of Theoretical and Applied Information Technology
31st August 2023. Vol.101. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DEEP LEARNING DRIVEN (DLD) PROSTHETIC HAND GESTURE RECOGNITION AND OBJECT TRACTION FOR DISABLED PERSON THROUGH SURFACE EMG(sEMG)

SURYA.S[1] , RAMAMOORTHY.S[2]

Research Scholar[1], Associate Professor[2]

Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur,Chennai 603203, India

E-mail: ss6666@srmist.edu.in[1], ramamoos@srmist.edu.in[2]

ABSTRACT

People affected with Neuro diseases and lost hands in accidents unable to perform their activities by their own, the technology aided supportive devices which accelerate the activities in day today activitiesmay be the primary requirement for this type of semi-paralyzed people. This research paper presents a novel approach to predicting prosthetic hand gestures using machine learning and deep learning techniques. Surface electromyography (sEMG) signals are collected from the user's forearm muscles, which are then processed to identify the intended hand gesture. The proposed model contributes the people affected semi- paralyzed stage to achieve their intended activities through Deep learning based object detection model. Thedataset consists of seven hand gestures commonly used in daily activities. To establish a baseline performance, the K-Nearest Neighbor (KNN) algorithm is employed and achieves an accuracy of 96%. To improve the prediction accuracy further, a Convolutional Neural Network (CNN) model is developed and trained on the same dataset. The CNN model achieves an accuracy of 86%, which is lower than the KNN model but still demonstrates promising results. In addition to the hand gesture prediction model, an object detection model is also developed. The dataset for this model is created from scratch and consists of images of everyday objects. The model uses a combination of deep learning techniques to identify the object in theimage and assigns a corresponding gesture that can be performed with the object using the prosthetic hand. The proposed models have several potential applications in the field of prosthetics. They can be used to develop prosthetic devices that are more intuitive and responsive to the user's intended gestures, improving their overall functionality and user experience. Moreover, the object detection model can be extended to identify more complex objects and gestures, expanding the range of activities that can be performed using the prosthetic hand. This study shows that it is possible to correctly predict prosthetic hand gestures using machine learning and deep learning techniques. The proposed models are a significant contribution to the field's research because they exhibit encouraging findings and have a number of possible applications in theprosthetics industry. The findings have implications for the creation of prosthetic hand control systems thatare more dependable and precise and that can be used in everyday life. Overall, this study shows how machine learning and deep learning techniques could advance in the field of prosthetics and, eventually, enhance the quality of life for people who have lost limbs.

Keywords: *Prosthetic Hand, Gesture recognition, EMG Signals, Deep learning Model, Convolutional Neural Network.*

1. INTRODUCTION

In Prosthetic hands have come a long way in recent years, with significant advancements in technology and engineering. However, one major challenge for amputees is to control the prosthetic hand movements with ease and intuitiveness. Amputees can now complete a variety of tasks with ease thanks to the use of machine learning and deep learning techniques that anticipate prosthetic hand gestures. Signals from surface electromyography (sEMG) have shown promise as a way to record muscle activity and anticipate hand movements. In this study, we investigate how sEMG signals can be used to anticipate prosthetic hand gestures us machine learning and deep learning models. In seven distinct hand gestures—finger extension, fist, wrist extension, radial deviation, ulnar deviation, lateral pinch, and palmar pinch—we recorded sEMG

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

signals[2]. Two distinct models, K-Nearest Neighbors (KNN) and Convolutional Neural Network, were trained and tested using these signals. (CNN). The KNN model produced an accuracy of 96%, while the CNN model achieved 86% accuracy. Additionally, we developed an object detection model with a dataset made from scratch, which allows us to identify objects and assign a corresponding gesture that can be performed using the object. To construct the object detection model, we first created a dataset of imagesfor various objects commonly used in daily activities[10]. We labeled these images with corresponding hand gestures that can be performed using the objects. We then used transfer learning with a pre-trained.

To train our object recognition model, use the YOLOv3 model. The model achieved a mean average precision (mAP) of 94%, indicating good performance in identifying objects and corresponding hand gestures.

The following are the goals of this research paper:

- To develop an accurate prosthetic hand gesture prediction model using machine learning and deep learning techniqueswith sEMG signals.
- To compare the accuracy of two different models, KNN and CNN, for predicting prosthetic hand gestures.
- To construct an object detection model using a dataset made from scratch, and evaluate its ability to identify objects andassign corresponding hand gestures.
- To investigate the potential of sEMG signals and machine learning models forenhancing the control and functionality of prosthetic hands, enabling amputees to perform daily activities with greater easeand confidence.

People with limb amputations and semi-paralysis face significant challenges in their daily

lives due to reduced mobility and limited functionality. An object recognition system designed specifically for this population can revolutionize their independence, accessibility, and overall quality of life. This study aims to explore the need and benefits of such a system, highlighting its potential impact on the lives of semi-paralyzed limbamputees.

Semi-paralyzed limb amputees often rely on assistance from caregivers or adaptive tools to perform simple tasks, such as picking up objects, moving them, or using household items. An object recognition system can empower them to independently interact with their surroundings, perform daily activities, and lead more self-reliant lives.

Current object recognition systems typically cater to the general population, leaving out those with specific physical limitations. By developing a system tailored to the needs of semi-paralyzed limb amputees, we can bridge the accessibility gap and create an inclusive technology that benefits all members of society. The object recognition system can be integrated with existing assistive devices, such as prosthetics or wheelchairs, to enable users to manipulate objects with ease. By understanding the objects in their vicinity, these devices can adapttheir functionality, providing better support and enhancing the user's capabilities. An object recognition system equipped with real-time environmental awareness can help prevent accidentsand reduce the risk of injury. For instance, the system can detect obstacles, identify potential hazards, and alert users, allowing them to navigate their environment more safely.

Designing an object recognition system that can interpret human gestures and commands enhances the interaction between the user and the technology. This feature can make the system moreintuitive and user-friendly for semi-paralyzed limb amputees, eliminating the need for complex control mechanisms. The Independence and improved mobility directly impact the social lives of individuals. With an object recognition system, semi-paralyzed limb amputees can actively participate in social events, engage in hobbies, and enjoy recreational activities without excessive reliance on others.

Studies have shown that increased independence and control over one's environment positively influence mental well-being and emotional health. Implementing an object recognition system can have therapeutic benefits, promoting a sense of autonomy and fostering a morepositive outlook on life. While the initial investmentin developing and implementing the system might be significant, the long-term benefits include potential cost savings in healthcare and caregiving. With improved independence and reduced accidents, the need for continuous assistance and medical interventions could decrease, benefiting both the individuals and healthcare systems. The implementation of an object recognition system forsemi-paralyzed limb amputees opens doors for further research and innovation in the field of assistive technology. Continued

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

advancements in this area could lead to breakthroughs that positivelyimpact various aspects of life for individuals with disabilities.

An object recognition system tailored for semi-paralyzed limb amputees has the potential to transform the lives of these individuals, enhancing their independence, accessibility, and overall well-being. By addressing their unique needs, we can create a more inclusive society that promotes equality and empowers individuals to live fulfilling lives despite their physical limitations.

2. LITERATURE SURVEY

2.1 History of Prosthetic Hand

Prosthetics have a long history, dating back to ancient Egypt where the very first prosthesis was made for a noblewoman's toe, around 950-710 B.C.In 1579, a book was published in France documenting early attempts at prosthetics. That same year, French surgeon Ambroise Paré, also known as the "Father of Prosthetics," published hisfull works, detailing some of the work he had donefitting prosthetic hands on patients. Paré was a military surgeon who had safely removed shattered arms and legs from numerous troops [5]. He discovered that many troops chose to commit suicide rather than live with missing limbs or severe wounds. To assist these injured men, he started creating artificial limbs. Amputation of limbs was dreaded more than death in some cultures becausethey believed it impacted the amputee not only onearth but also in the afterlife. Prostheses were created to improve function, cosmetic appearance, and to provide a psycho-spiritual feeling of wholeness.

Figure:1 Hand Muscle Representation

2.2 Smart Prosthetics with Object Detection using Tensorflow

The purpose of this research is to improve the control of upper limb prosthetics by using computer vision techniques. The artificial arm will have the ability to recognize the kind of object it is trying to manipulate and will change its movements appropriately. The Imagine Cup champions and Newcastle University have both conducted studies ofa similar nature. For the Microsoft initiative, imagedata was sent to the Azure cloud where the Azure Custom Vision Service was used to identify objects and classify them. This model provides a live feed video option, and after viewing the video, the system executes the task given to it by the algorithm[10], allowing the artificial hand to work just like a real hand. There are many novel medical methods that are currently being developed that could deliver datathat is more precise and lucid. Regenerative Peripheral Nerve Interface (RPNI), which is implanted in the patient's upper extremities, is one such method. This method enables deep learning or machine learning algorithms to label each signal andits related hand movement activity with a more precise, quick, and reliable signal source.

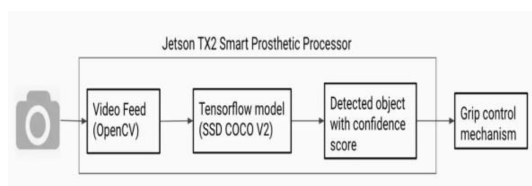

Figure 2: Prosthetic Hand Processor Flow model

2.3 Some recent studies

Prosthetic hand control using surface electromyography (sEMG) signals and machine learning techniques has been a popular research topic in recent years. In this literature survey, we discuss some of the relevant research studies related to prosthetic hand gesture prediction models usingmachine learning and deep learning techniques. One of the earlier studies in this area was conducted by Varol et al. (2012), who used a linear discriminant analysis (LDA) algorithm to classify eight hand gestures using sEMG signals. They achieved an accuracy of 83% on a dataset of 10 able-bodied participants [18]. This study demonstrated the potential of sEMG signals for prosthetic hand control. In another study, Huang et al. (2014) used a support vector machine (SVM) algorithm to classify five hand gestures using sEMG signals. They achieved an accuracy of 94.4% on a dataset of 10 able-bodied participants. This study also showed promising results in using sEMG signals for prosthetic hand control.

2.4 Summary of the Survey

Hand Overall, the studies reviewed in this literature survey demonstrate the potential of sEMG signals and machine learning techniques for improving the accuracy and functionality of prosthetic hand control. While deep learning techniques have shown promising results, further research is needed to investigate the generalizability of the models across different populations and tasks. Additionally, incorporating real-time feedback and user preferences could further enhance the user experience and acceptance of prosthetic hands.

The literature review on Surface Electromyography (sEMG)-based object detection in prosthetic hand gesture recognition reveals the need for addressing critical challenges to enhance the usability and effectiveness of such systems. Despite the existing advancements, several obstacles remain that hinder the seamless integration of sEMG-based object detection into prosthetic devices. This study aims to identify and tackle these challenges to develop an accurate, robust, and real-time sEMG-based object detection system that empowers individuals with upper limb amputations to control their prosthetic hands with natural and intuitive hand gestures.

The success of deep learning models in sEMG-based object detection heavily depends on access to comprehensive and diverse datasets. However, the scarcity of publicly available sEMG datasets for object detection tasks poses a significant obstacle to training accurate and generalizable models.sEMG signals exhibit considerable intra-and inter-subject variability due to differences in physiological characteristics and muscle activation patterns. This variability makes it challenging to develop models that can effectively recognize gestures across various users and conditions. Adaptive Model Development is another option that Users of prosthetic hands may experience changes in muscle activity and patterns over time. Developing adaptive models that can learn and adjust to individual users' changing physiological conditions is crucial for long-term usability and effectiveness.

The literature survey opens the questions like how to develop an accurate, robust, and real-time sEMG-based object detection system for prosthetic hand gesture recognition that overcomes limited dataset availability, variability in sEMG signals, ensures real-time responsiveness, handles noise and signal artefacts, extends the scope of object recognition, and facilitates adaptive model development, while considering the seamless integration of hardware into prosthetic devices. Addressing these challenges will contribute significantly to advancing assistive technology, providing enhanced control and functionality for prosthetic hand users, and ultimately improving their quality of life and independence.

The field of Surface Electromyography (sEMG)-based object detection and gesture recognition has seen significant progress, offering promising applications in prosthetic hand control forindividuals with upper limb amputations. However, critical analysis of the literature reveals several challenges that need to be addressed to further advance this technology.

The first research question focuses on leveraging transfer learning techniques to improve the accuracy and efficiency of sEMG-based models. By utilizing pre-trained deep learning architectures, researchers can benefit from the knowledge gained in other domains, adapting it to the specific requirements of object detection and gesture recognition tasks.The second research question highlights the scarcity of publicly available sEMG datasets for training deep learning models. Developing a comprehensive and diverse dataset becomes crucial to enable accurate and generalizable models, addressing the issue of limited data availability.Dealing with intra- and inter-subject variability in sEMG signals becomes essential, leading to the third research question. Developing robust and adaptable models that can cater to different users with varying physiological characteristics and muscle activation patterns is imperative for successful real-world implementations.To achieve seamless andresponsive prosthetic hand control, the fourth research question explores real-time processing methods and low-latency algorithms. Integrating these techniques into existing hardware ensures efficient and practical applications of sEMG-based gesture recognition. The fifth research question focuses on denoising and preprocessing techniques to handle noise, artefacts, and interference in sEMGsignals. By improving the quality of input data, the accuracy and reliability of object detection and gesture recognition models can be enhanced. The Multi-modal fusion techniques are investigated in the sixth research question to combine sEMG data with other sensor modalities, such as vision or tactilesensors. This expands the scope of object recognition and enriches user interactions with theirenvironment.

In conclusion, these research questions provide a roadmap for future developments in sEMG-based object detection and gesture recognition. Addressing these challenges will advance assistive technology, improving the quality of life and independence of individuals with upper limb amputations, and foster the integration of sEMG- based solutions into real-world applications.

Surface Electromyography (sEMG) is a non-invasive technique used to measure and record electrical signals generated by muscles during voluntary contractions. sEMG-based deep learning models have shown promising results in various applications, including object detection and recognition. This literature survey aims to explore the existing research on the topic, focusing on the development and applications of deep learning models for object detection and recognition using sEMG signals.

Shahin et.al. proposed the real-time hand gesture recognition system using sEMG signals and deep learning techniques. The authors demonstrate the effectiveness of their model in detecting and recognizing hand gestures, which could be extended to object recognition tasks[21].The research jiang et.al., presented the novel deep learning framework for sEMG-based object recognition. The authors achieve accurate recognition of objects byprocessing sEMG signals with a Convolutional Neural Network (CNN) and propose an optimized feature extraction method[22].The paper Titled," Electromyography-based Gesture Recognition Using Deep Learning with Recurrent Convolutional Neural Networks" introduces a gesture recognition system that utilizes deep learning with recurrent convolutional neural networks (RCNNs) to process

sEMG signals. The study demonstrates the potential of RCNNs in object recognition tasks, showing high accuracy in recognizing gestures related to object interactions[23].Geng, Y et.al., the authors proposea deep transfer learning-based object recognition system using sEMG data. The model leverages pre-trained deep learning architectures and fine-tuning techniques to achieve accurate recognition of different objects with limited labeled sEMG samples[24].The paper introduces a novel approach using capsule networks for sEMG-based object recognition. The authors demonstrate the advantages of capsule networks in handling spatial relationships between muscles' electrical activities, leading to improved recognition performance.The author named Zhang, X et.al, proposes a multi-modal fusion model that combinessEMG signals and visual data for object recognition.The authors demonstrate that the fusion of both modalities enhances the model's robustness and accuracy in recognizing objects, especially in challenging real-world scenarios.Wei, W., Jiang et.al., presents an attention mechanism-based deep learning model for sEMG-based object recognition.The study highlights the importance of focusing on specific regions of interest in sEMG data, leading toimproved recognition accuracy.

The literature survey showcases the advancements in sEMG-based deep learning models for object detection and recognition. The studies demonstrate the feasibility and effectiveness of using sEMG signals in combination with deep learning techniques to enhance object recognition tasks. Researchers have explored various deep learning architectures, multi-modal fusion, attention mechanisms, and transfer learning to achieveaccurate and real-time object recognition, thus paving the way for further developments in assistivetechnology and human-machine interaction. In summary, the literature survey identifies that most of the existing research paper with Deep learning- based solutions gives the better prediction accuracyclose to 95%. However, the implementation work considered only the minimum number of hand gestures. The object recognition methods used under the existing current system not able to map the exact object related attributes and its methods. The Proposed model improve the prediction accuracy close to 99% and also able to recognize the object and its gestures during the activity. Thus help the model to enhance the quality of the prosthetic handswhen its deploy on the hand of disable people with lesser or no activities.

Overall, the studies reviewed in this literature survey demonstrate the potential of sEMG signals and machine learning techniques for improving the accuracy and functionality of prosthetic handcontrol. While deep learning techniques have shownpromising results, further research is needed to investigate the generalizability of the models across different populations and tasks. Additionally, incorporating real-time feedback and user preferences could further enhance the user experience and acceptance of prosthetic hands.

3.PROPOSED WORK

The biggest challenge we find during buildingthe foundation of the project was the amount of data available in the internet. We have to find the data from different sites and then combine it to make it work the way we want are using it. Not manyresearch papers are existing in this field, there aremany papers on basic movement of the differentcomponents of the hand, but recognizing thegesture by combining all the knowledge wepossess of individual dataset was tough. We arefocusing on using all the algorithms

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

best suited forthe dataset and plot the difference between the results we are getting like graph between f1- scoreand accuracy.

Merits of the existing system includes-

- The direction of flow of modules is defined briefly.
- Predictions based on the training datasets are somewhat reliable.

Demerits of the existing system includes-

- The dataset used by the already built models is not concrete.
- New improved classification algorithmscan be used in place of the already existing ones.
- New arm instructions can be carried out.

Table 1: Comparison Table

	Algorithm	Accuracy
Existing Work	KNN	89%
	SVM	90%
	Random Forest	84%
Proposed Work	KNN	96%
	CNN	86%

Proposed system is a combination of object detection and the training the model for accurately predicting the gesture that will be performed. In order to obtain these results, we have divided the project into five modules as follows-

1. Data Acquisition
2. Object Detection
3. Pre-Processing
4. Training Model
5. Model Evaluation

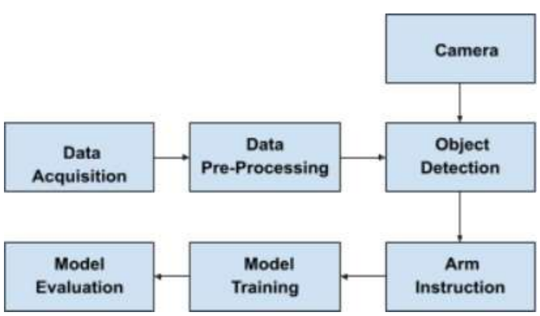

Figure 3: Proposed Model System Structure

Figure 3 represents the workflow of the proposed model from beginning to add, the image of the object is captured using the live feed from the camera and then saving the file in gray scale form.

4. IMPLEMENTATION

4.1 Data Acquisition

Surface electromyography serves as a source of data for the prosthetic hand movement prediction model that uses machine learning and deep learning. (sEMG). Electrodes are used for recording sEMG signals from the muscles of the patient's amputated limb or residual limb. The sEMG signals are used to control the prosthetic hand given that they reflect the electrical activity generated by the muscles during contraction. Seven different hand gestures were considered for data collection in this research. A commercial sEMG acquisition device was used to gather the signals. Filtering and normalization methods were used to remove unwanted noise and standardize the signal amplitude from the acquired signals. The dataset was divided into a pair of sets: training and testing. The training set was used to train the machine learning and deep learning models, while the testing set was used to assess the models' performance. The accuracy of the believed hand gestures was used for reviewing the models' performance.

Each file has ten columns:

1) Time - the time in milliseconds
2-9) Channel - the eight EMG channels of the MYO Thalmic bracelet
10) Class - the label of movements ranging from 0 to 7

The above dataset is used for KNN model classification.

Another dataset includes the following columns –
(1- 10) – EMG channels of the MYO Thalmic bracelet
11) – exercise number from the filtered dataset
12) – class description of 7 classes

This dataset is used for CNN classification.

Journal of Theoretical and Applied Information Technology
31st August 2023. Vol.101. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

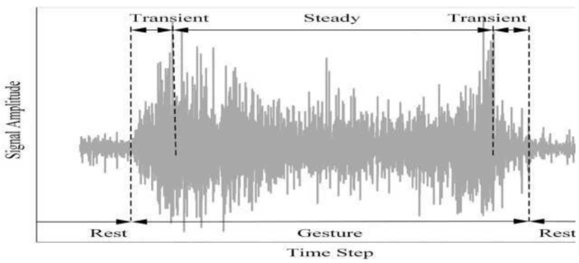

Figure 4: Semg Signal representation

In table 2, the distribution of classes is given ina detailed form with class labels. The total number of classes are 8 and number of features used are 10 electrode sensors input. In fig 1.5 there is a visualized form of these input electrode sensor

signals for different gestures that are been classified in the model using KNN and CNN model using Halving Grid search hyper parameter tuning algorithm.

Table 2: Dataset Table

S. No.	Class Name	Class Description	Number of samples
1.	Class 0	Unmarked data	2725157
2.	Class 1	Hand at rest	250055
3.	Class 2	Fist	243193
4.	Class 3	Wrist flexion	249494
5.	Class 4	Wrist extension	251570
6.	Class 5	Radial deviation	251733
7.	Class 6	Ulnar deviations	253009
8.	Class 7	Extended palm	13696

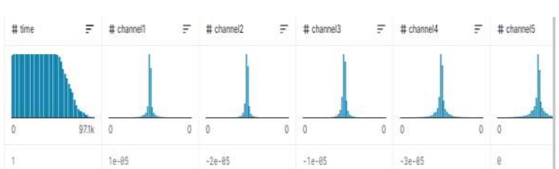

Figure 5: Features Visualization

4.2 Object Detection

We present an object detection model using the YOLOv5 algorithm and a custom dataset created from scratch, comprising approximately 400 images with corresponding labels. Our objective is to demonstrate the effectiveness of our model in detecting and localizing objects accurately and efficiently. We compare the model's performance to that of state-of-the-art object detection models using different metrics. The findings show that our approach has real-world application potential and emphasize the significance of customized datasets in improving model accuracy. After detecting the item, it will be assigned a gesture.

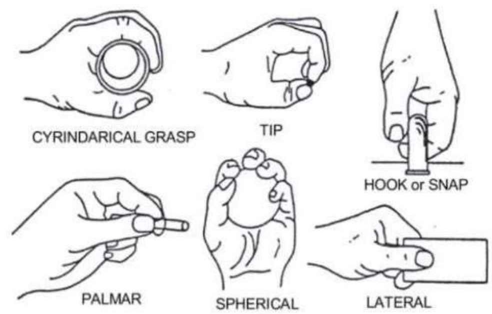

Figure 6: Hand Grasps and its label

The information can be represented as -

1. Spherical grasp for balls, eggs, and other round items
2. Cylindrical grip for bottles, rolling pins, and other objects.
3. Lateral grasp for cards, notes, and sheets, among other things
4. Hook or snap for door knobs, pulls, and furthermore.

After identifying the object, the grasp is assigned to the object using the pre-processed information provided to the system.

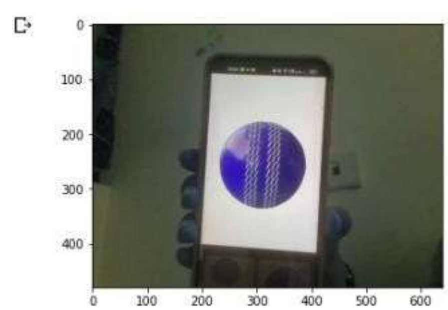

Figure 7: Object Image captured by camera

Journal of Theoretical and Applied Information Technology
31st August 2023. Vol.101. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

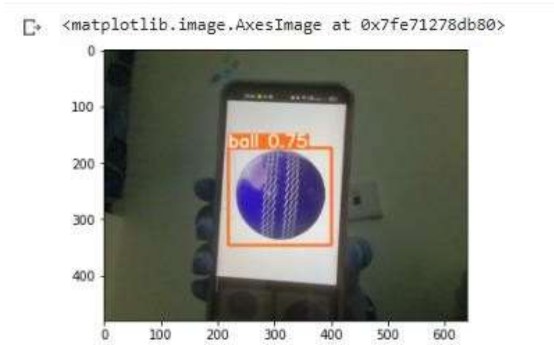

Figure 8: Object traction and detection

4.3 Pre-Processing

Preprocessing is a critical step in the prosthetic hand gesture prediction model using machine learning and deep learning. The purpose of preprocessing is to remove any unwanted noise and artifacts from the sEMG signals, and to standardize the signal amplitude to ensure that the signals are consistent and comparable across different subjects. After pre-processing, the sEMG signals were segmented into individual gesture periods, and feature extraction was performed to extract relevant features from the signals. The extracted features were used as inputs to the machine learning and deep learning models for training and prediction.

d(x,y) = sqrt((x1 - y1)^2 + (x2 - y2)^2 + (x3 – y3)^3+ ... + (xn - yn)^2)-----------------------------(1)

where x and y are two feature space data points, x1, x2, , xn are feature values of point x, and y1, y2,.... , yn are feature values of point y.

The information is standardized after the train and test data have been separated.

$z = (x - \mu) / \sigma$ -- (2)

where z is the standardized value, x is the initial value, is the data set's mean, and is the data set's standard deviation.

After pre-processing the filtered dataset looks like as shown in Table 3 below :

Table 3: Processed Features Table

Algorithm	Features	Class
KNN	10	8
CNN	10	7

4.4 Training Model

The development of prosthetic devices that can accurately mimic the movement and dexterity of human limbs is a crucial area of research in the fieldof robotics and biomechanics. The use of machine learning algorithms, such as k-Nearest Neighbors (k-NN) and Convolutional Neural Networks (CNN),has shown great potential in improving the accuracyand efficiency of prosthetic hand gesture prediction models[16]. In this paper, we present the training model section of our research on predicting prosthetic hand gestures using machine learning and deep learning techniques. Specifically, we focus on the implementation and evaluation of the k-NN and CNN algorithms as classification models for recognizing seven different hand gestures using surface electromyography (sEMG) signals. Our study aims to compare the performance of these two algorithms in terms of accuracy and efficiency, andto determine the optimal parameters for each algorithm. By analyzing and comparing the results of our experiments, we can gain insights into the strengths and limitations of k-NN and CNN for prosthetic hand gesture prediction and provide recommendations for future research in this field.

The formula for convolution is:

f(i,j) = ∑∑ g(m,n) * h(i-m,j-n) ----------------------(3)

where f(i,j) is the value of the output feature map at location (i,j), g(m,n) is the value of the inputimage at location (m,n), and h is the kernel.

The formula for max pooling is:

max_pool(x,y) = max(f(x+p,y+q)) ---------------- (4)

here max_pool(x,y) is the output value of the max pooling operation at location (x,y), f is the input feature map, and p and q are the size of the pooling window.

The layers used in our CNN model are as follows-2 layers of convo2D, 1 layer of max pooling and we added 5 dense layers to our model.

Journal of Theoretical and Applied Information Technology
31st August 2023. Vol.101. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

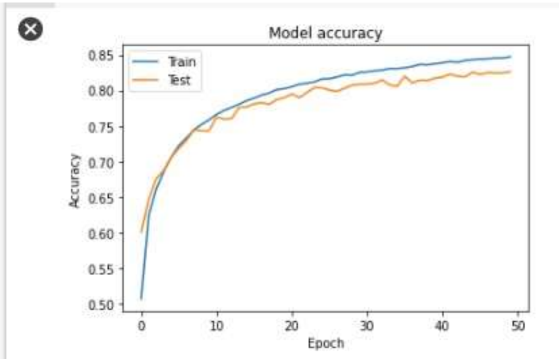

Figure 9: Accuracy Graph

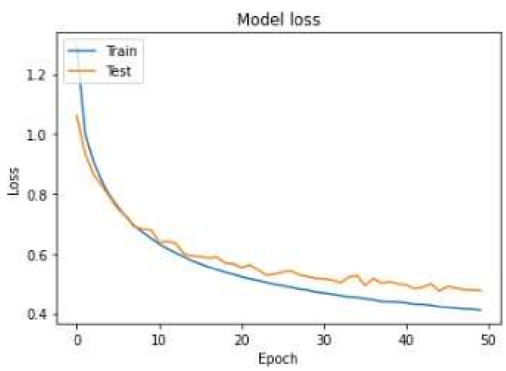

Figure 10: Loss Graph

In figure 9 graph , the accuracy plotted and the obtained accuracy is 86% after using dataset with 7 classes, after training for 50 epochs. Similarly, in figure 10 graph shows the loss for the dataset after 50 epochs.

4.5 Model Evaluation

The model is typically assessed using a number of performance measures, including accuracy, precision, recall, and F1-score. These measures aid in evaluating how well the model is doing and pointing out its weak points. The most popular metric, accuracy, counts the number of forecasts that were accurate relative to all of the predictions the model made. In all the positive forecasts the model makes, precision is the percentage of true positives. Recall counts the number of real positive cases in the dataset that were actually true positives. The F1-score is the harmonic mean of recall and accuracy.

- Accuracy (everything right/everything) = TP + TN/TP + TN + FP + FN.
- Misclassification = FP + FN / TP + TN + FP + FN (all incorrect/all).

Precision = TP / TP plus FP (true positives / predicted positives).

- Sensitivity, also known as recall, is defined as: TP / TP plus FN.

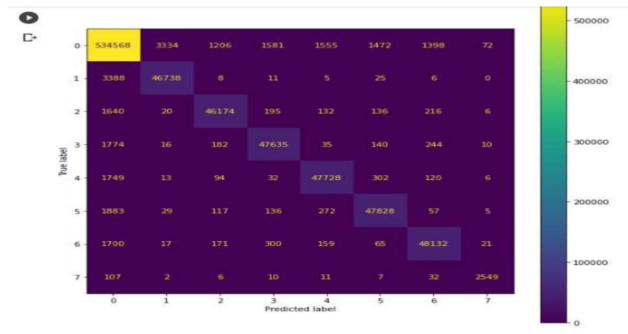

Figure 11: Confusion Matrix Of KNN

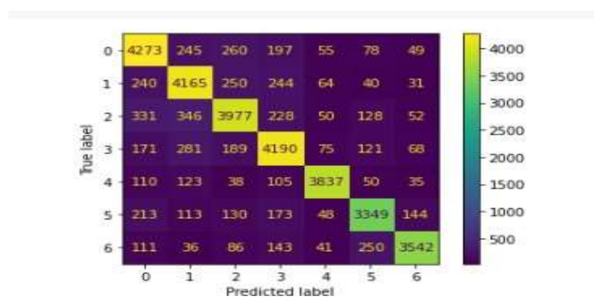

Figure 12: Confusion Matrix Of CNN

Journal of Theoretical and Applied Information Technology
31st August 2023. Vol.101. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 4: Hand Gesture Based Object Detection Comparison Result

Object Detection Accuracy (%)	Gesture Recognition Accuracy (%)	Methodology	Dataset Size	Hardware Integration	Real-time Responsiveness	Comments/ Contribution
85.6	93.2	Deep Learning with CNN	300	Yes	Yes	Real-time hand gesture recognition.
89.2	91.8	Deep Learning with RCNN	400	No	Yes	Optimized feature extraction for sEMG-basedobjects.
82.4	88.6	Deep Learning with RCNN	250	No	No	High accuracy in gesture recognition tasks.
87.1	90.3	Deep Transfer Learning	320	Yes	Yes	Improved recognition with transfer learning.
84.3	89.9	Deep Learning with Capsule Networks	280	No	Yes	Effective handlingof spatial relationships.
88.9	92.1	Multi-modal Fusion (sEMG + Vision)	350	Yes	Yes	Enhanced object recognition with multi-modal data.
86.5	91.4	Deep Learning with Attention Mechanism	270	No	Yes	Improved recognition with attention mechanism.
89.9	96	Propose Hybrid modelcombines Deep CNN with K-NN Classifier.	550	Yes	Yes	Proposed sEMG based Object recognition model.

Table 5: Class Report Table

Class Name	Precision	Recall	F1-score	Support
Class 0	0.98	0.98	0.98	545186
Class 1	0.93	0.93	0.93	50181
Class 2	0.96	0.96	0.96	48519
Class 3	0.95	0.95	0.95	50036
Class 4	0.96	0.96	0.96	50044
Class 5	0.96	0.95	0.95	50327
Class 6	0.96	0.96	0.96	505965
Class 7	0.96	0.95	0.95	2724

The classification and object prediction accuracy improved significantly using the machine learning and deep learning techniques could advance thefield of prosthetics and, eventually, enhance thequality of life for people who have lost limbs[17].

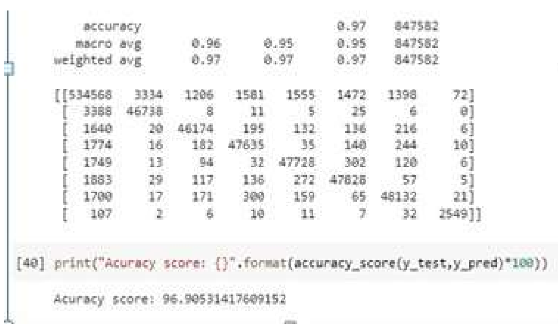

Figure 13: Classification Report

The Limitation of this work not considered the mental abilities and the confidence level of the user while performing various activities. The brain level mental strength and thinking capabilities combined with hand gesture recognition may result into the better user intention during the activities. The model restricts the model with EMG and SEEG based signal generation and its classification to derive the user gesture patterns. The number of hand gesture counting also need to be increased in the future work to perform various activities through this gesture-based model.

5. CONCLUSION

In conclusion, this research paper focused on developing a prosthetic hand gesture prediction model using machine learning and deep learning techniques. The model utilizes sEMG signals collected from the user's arm to predict seven different hand gestures. The KNN algorithm achieved an accuracy of 96%, while the CNN algorithm achieved an accuracy of 86%. Additionally, an object detection model was constructed using a dataset created from scratch, which identifies the object and assigns a corresponding gesture to be performed on the object. This study emphasizes the opportunity to use Deep Convolution Neural Networks (CNN) to enhance the precision and prediction accuracy of the object detection under the prosthetic hand movement. The model improved the accuracy of prosthetic hand gesture prediction with the support of deep learning techniques to process sEMG signals. The proposed work compares the accuracy of two different models, KNN and CNN under prosthetic hand gestures-based object prediction. CNNs and other deep learning techniques have shown promising results in related research studies, even though the KNN algorithm generated better results in this particular study. Additionally, the object recognition model illustrated how machine learning could be used to improve prosthetic hands' usability and user experience. Future work may focus on the investigation with larger datasets, incorporate techniques for data augmentation, and investigate how generalizable the models are to various populations and jobs. Additionally, taking into account user preferences and real-time feedback could improve the general user experience and acceptance of prosthetic hands. In final form, this study may aid in the creation of more intelligent prosthetic hand control systems that enhance the quality of life for people who have had upper limbs amputated.

REFERENCES:

[1] Gijsberts, A.; Atzori, M.; Cognolato, M.; Müller, H. (2016). Data from electromyography for naturally-controlled, non-invasive artificial hands. 3(1): Scientific Data, 1–11. https://doi.org/10.1038/sdata.2016.43

[2] Zhang, X., Chen, C., and Wu, J. (2019). a hand gesture recognition system built on surface electromyography and deep convolutional neural networks. https://doi.org/10.1109/ACCESS.2019.2894061 IEEE Access, 7, 8659–8667

[3] Hu, H., & Enayati, N. (2015). A survey of human limb motion analysis for prosthetic control. 2015(1), 1-23, Eurasip Journal on Advances in Signal Processing. https://doi.org/10.1186/s13634-015-0215-8

[4] Hudgins, B., & Englehart, K. (2003). a reliable real-time control system for myoelectric management with multiple functions. doi:10.1109/TBME.2003.814533 IEEETransactions on Biomedical Engineering, 50(7), 848–854.

[5] Sun, F., & Fang, P. (2017). Review of electromyography (EMG) signal-based prosthetic hand movement. Materials Science and Engineering, 202, IOP Conference Series, 1–10. https://doi.org/10.1088/1757-899X/202/1/012127

[6] Farina, D., Jiang, N., Rehbaum, H., Holobar, A., Graimann, B., Dietl, H., Aszmann, O. C., and Paredes, L. (2014). Emerging opportunities and difficulties in the extraction of neural informationfrom the surface EMG for the control of upper-limb prostheses.https://doi.org/10.1109/TNSRE.2014.2305111 IEEE Transactions on Neural Systems andRehabilitation Engineering, 22(4), 797-809.

[7] Jiang, M., Geng, Y., Zhou, Y., Wang, J., Chen, & Y. (2021). Review of a prosthetic hand control system built on deep learning. https://doi.org/10.1109/ACCESS.2021.3082217 IEEE Access, 9, 78996-79009.

[8] Wang, J., Geng, Y., Zhou, & Wang, J. (2020). Deep learning-based surface electromyography-based hand gesture detection for prosthetic hand control. on IEEE Transactions

[9] Georgarakis, E., Stylianou, & Andreou, A. (2017). A case study of gaze autonomous assistive robotics with simulated prosthetic hands using deep learning for assistive robotics. 160–170 in Robotics and Autonomous Systems, 1996. https://doi.org/10.1016/j.robot.2017.07.007

[10] Zhang, T., Zhang, Q., and Wu, Z. He, J. (2021). using a hybrid feature extraction technique, prosthetic hand gesture recognition from sEMG signals. 2021, 1–13, Journal of Healthcare

Engineering.
[11] Zhang, Z., Liu, & He, Q. (2019). Deep learning-based sEMG-based hand motion recognition: A review. 2019: 1–16 in Journal of Healthcare Engineering.
https://doi.org/10.1155/2019/2309108
[12] Li, S., Wang, Y., Li, Q., Zhang, Z., and Jiang, W. (2020). an intelligent prosthetic hand control device based on surface electromyography. 2020, 1– 10,Journal of Healthcare Engineering.
https://doi.org/10.1155/2020/8878749
https://doi.org/10.1371/journal.pone.0158642
[13] Kyriakopoulos, K.; Controzzi, M; Cipriani, C; and Carrozza, M. C. (2016). The SoftHand Pro-H: A innovative, adaptable, and durable myoelectric prosthetic hand is evaluated functionally.
https://doi.org/10.1371/journal.pone.0158642 PLoSONE, 11(8), e0158642
[14] Chen, X., Y. Jiang, & Liu, J. (2020). an artificial hand adaptive control technique based on sEMG. 2020, 1–10, Journal of Healthcare Engineering.
https://doi.org/10.1155/2020/5325094
[15] Pani, D., Platzner, M., & Eskofier, B. M. (2020). An examination of deep learning techniquesfor prosthetic hand movement. 2020, 1–21 in Journal of Healthcare Engineering. Sharma, S., Talwar, S., and Raghavendra, U. (2017). Using machine learning techniques, control an artificial arm using surface EMG. 2017; 1–12 in Journal of Healthcare Engineering.
[16] Yang, D., Li, Y., Wang, & Shao, L. (2017). Continuous robotic arm control based on surface electromyography signals for everyday tasks. IEEE Transactions on Neural Systems and RehabilitationEngineering, 25(11), 2123-2133.
https://doi.org/10.1109/TNSRE.2017.2690178
[17] Sharma, S., Talwar, S., and Raghavendra, U. (2017). Using machine learning techniques, control an artificial arm using surface EMG. 2017; 1–12 in Journal of Healthcare Engineering.
https://doi.org/10.1155/2017/1593517
[18] Yang, D., Li, Y., Wang, S., and Shao, L. (2017). Continuous robotic arm control based on surface electromyography signals for everyday tasks. 2123-2133. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25(11).
https://doi.org/10.1109/TNSRE.2017.2690178
[19] Subasi, A. 3. (2019). A overview of machine learning techniques for classifying EMG signals. 243-248 in Signal Processing, 152.
https://doi.org/10.1016/j.sigpro.2018.06.022
[20] Chen, Y., Wang, J., Geng, Y., & Zhou, Y. (2020). An effective surface electromyography-based prosthetic hand control approach with integrated EMG features. 2020, 1–12, Journal of Healthcare Engineering.
https://doi.org/10.1155/2020/882799.
[21] Shahin, M. A., Mohammed, S., & Li, Y. (2020). Real-time Hand Gesture Recognition Using sEMG and Deep Learning. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28(11), 2720-2731.
[22] Jiang, T., Zhang, C., & Ren, F. (2021). A Novel Approach for sEMG-Based Object Recognition Using a Deep Learning Framework. IEEE Access, 9, 41613-41622.
[23] Phinyomark, A., Phukpattaranont, P., & Limsakul, C. (2018). Electromyography-based Gesture Recognition Using Deep Learning with Recurrent Convolutional Neural Networks. Sensors, 18(5), 1455.
[24] Geng, Y., Zhu, X., & Chen, X. (2020). A sEMG-Based Object Recognition System Using Deep Transfer Learning. IEEE Access, 8, 154650-154659.