Gesture Based Control Of Mechanical Arm Using Wearable IMU Sensors

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***Abstract—* Gesture has played an important role in reducing the gap between human and machine. Hand gesture recognition is applied in many technologies like games, wireless devices, mobile application, etc. In this paper, we have proposed a system in which the mechanical arm imitates the gesture performed by the operator using a wearable and machine learning algorithm for classification of gestures. The wearable is based on Inertial Measurement Unit (IMU) sensors which is gaining significant importance in field of Gesture Recognition. The classification algorithm used is Support Vector Machine which can recognize movement with less computation time and higher accuracy, and can also model non-linear relation with more precise classification using SVM kernels.**

***Index Terms—* Gesture Classification, IMU sensors, Wearable device, Mechanical arm, Human-machine Interaction.**

I. INTRODUCTION

Human-Machine Interaction (HMI) is a widespread field that studies communication between human and machine. HMI is the interaction between human and machine which is done by analyzing human behavior and appearance Various methods are proposed in human machine interaction. Some of them are through voice, keyboard, camera, etc. Gesture is one of the methods used for HMI which is a non-verbal communication method based on body movements. Inertial sensor based gesture recognition is gaining popularity because of its low cost, lightweight, low power design with great precision. Inertial measurement unit (IMU) consists of accelerometer and gyroscope responsible for finding the positioning of an object in 3D space. These sensors would help in finding positioning co-ordinates of hand movement. Briefly, in this paper we have proposed a system in which the mechanical arm imitates the gesture of the operator. The gesture data is collected through an Inertial Measurement Unit (IMU) which consists of a 3-axis gyroscope and accelerometer. A virtual reality head gear helps in viewing the workspace through a camera situated there. Among popular classification algorithms it is found out that Support Vector Machine (SVM) is proven to recognize gestures in less computation time with higher accuracy rate. The input to classifier is the data from IMU sensors and its output is the corresponding label which defines the action performed by the mechanical arm. The wearable and mechanical arm are connected to a computer wirelessly through Bluetooth. The machine learning algorithm can be run on the computer and the output of the algorithm will be passed to Raspberry Pi that controls mechanical arm.

A] Gesture Classification

A lot of work has been done in the field of human face expression recognition which is an active research topic since the early nineties. There has been a lot of advances in the past few years for face detection and tracking while the problem of recognizing hand gestures is under explored. The reason is the higher level of complexity of hand gestures as compared to face detection. Hand gestures can be recorded using devices like depth cameras or data gloves equipped with sensors. Use of cameras and image processing introduces complex computations which may be difficult to overcome hence gloves equipped with sensors are ideally suited for this task .

There are a lot of fields of work like nuclear power plants, underwater exploration, disaster prone areas or other places where human intervention is difficult or there are situations where the machine operator has to control machine through long distance. Traditional methods like remote control would be tough to handle in those conditions. In such situations gesture based control of the machine helps in handling it easily where machines like mechanical arm would imitate the gesture of the operator and the work could be performed from a distance.

Briefly, in this paper we have proposed a system in which the mechanical arm imitates the gesture of the operator. The gesture data is collected through an Inertial Measurement Unit (IMU) which consists of a 3-axis gyroscope and accelerometer. A virtual reality head gear helps in viewing the workspace through a camera situated there. Among popular classification algorithms it is found out that Support Vector Machine (SVM) is proven to recognize gestures in less computation time with higher accuracy rate. The input to classifier is the data from IMU sensors and its output is the corresponding label which defines the action performed by the mechanical arm. The wearable and mechanical arm are connected to a computer wirelessly through Bluetooth. The machine learning algorithm can be run on the computer and the output of the algorithm will be passed to Raspberry Pi that controls mechanical arm.

II. LITERATURE REVIEW

A] Hand Body Language Gesture Recognition Based on Signals From Specialized Glove and Machine Learning Algorithms

[1] Paweł Pławiak et al. This paper presents a system for quick and effective recognition of hand gestures based on data glove equipped with 10 sensors. Collected data was preprocessed using normalization and PCA analysis to test increase in classification sensitivity with reduction of data. They designed models using 3 machine learning algorithms based on Neural Network, Support Vector machine and K-nearest neighbors. Through results they found out that SVM gave highest accuracy rate (98.32%) as compared to PNN (97.23%) and KNN (97.36%). They have applied resampling at the beginning of pre-processing to

reduce volume of data that didn't cause any negative effects on classifiers performance. Normalisation was used to convert data into the expected range of -1 to 1.

B] An Efficient Approach to Recognize Hand Gestures Using Machine-Learning Algorithms

[2] Md Ferdous Wahid et al. This paper presents use of Electromyography (EMG) sensors for capturing gesture data. Five machine learning algorithms such as K-nearest neighbor (KNN), Discriminant analysis (DA), Naive Bayes , Random Forest and Support Vector Machine (SVM) were used to classify 3 different hand gestures. SVM showed maximum accuracy (97.56%) in classification which was further improved by normalizing EMG features (98.73). The EMG data was collected from five subjects having ages in the range of 27 to 37 years. Mean absolute value, waveform length, zero crossing and slope sign change were extracted which were found to be robust for classification. All these features had correlation coefficient greater than 0.3 and were normalized. Ranking analysis was performed on all the features which showed that normalized EMG features gave better results as compared to actual EMG features.

C] Artificial Neural Networks for Gesture Classification with Inertial Motion Sensing Armbands

[3] Ananta Srisuphab et al. This paper presents the design of an automated tool to assist construction workers in the hand signal communicative channel. This system uses Myo sensors which is a combination of surface Electromyography (EMG) and Inertial Measurement Unit (IMU). The algorithm used for classification is Multi-Layer Neural Network. Daubechies wavelet transforms was used to analyze in frequency domain along with normalization and 10-fold cross validation was performed. The highest mean classification accuracy achieved was 88.176%.

D] Training CNNs for 3D Sign Language Recognition with color texture coded Joint Angular Displacement Maps

[4] E.Kiran Kumar et al. In this paper Convolutional Neural Network (CNN) is used in the recognition of 3D motion-captured sign language. The 3D information of each sign is interpreted using Joint Angular Displacement maps (JADM) which uses both angular measurements and joint distance maps (JDM) and encodes skeletal data into color texture images.

E] Imitation and Learning of Human Hand Gesture Tasks of the 3D Printed Robotic Hand by Using Artificial Neural Networks

[5] Mehmet Celalettin Ergene et al. In this paper it is explained how robot hand can learn via imitation using image processing based on Artificial Neural network. Features were extracted using image processing algorithms such as filtering and background subtraction. The success rate of network is 90.1%.

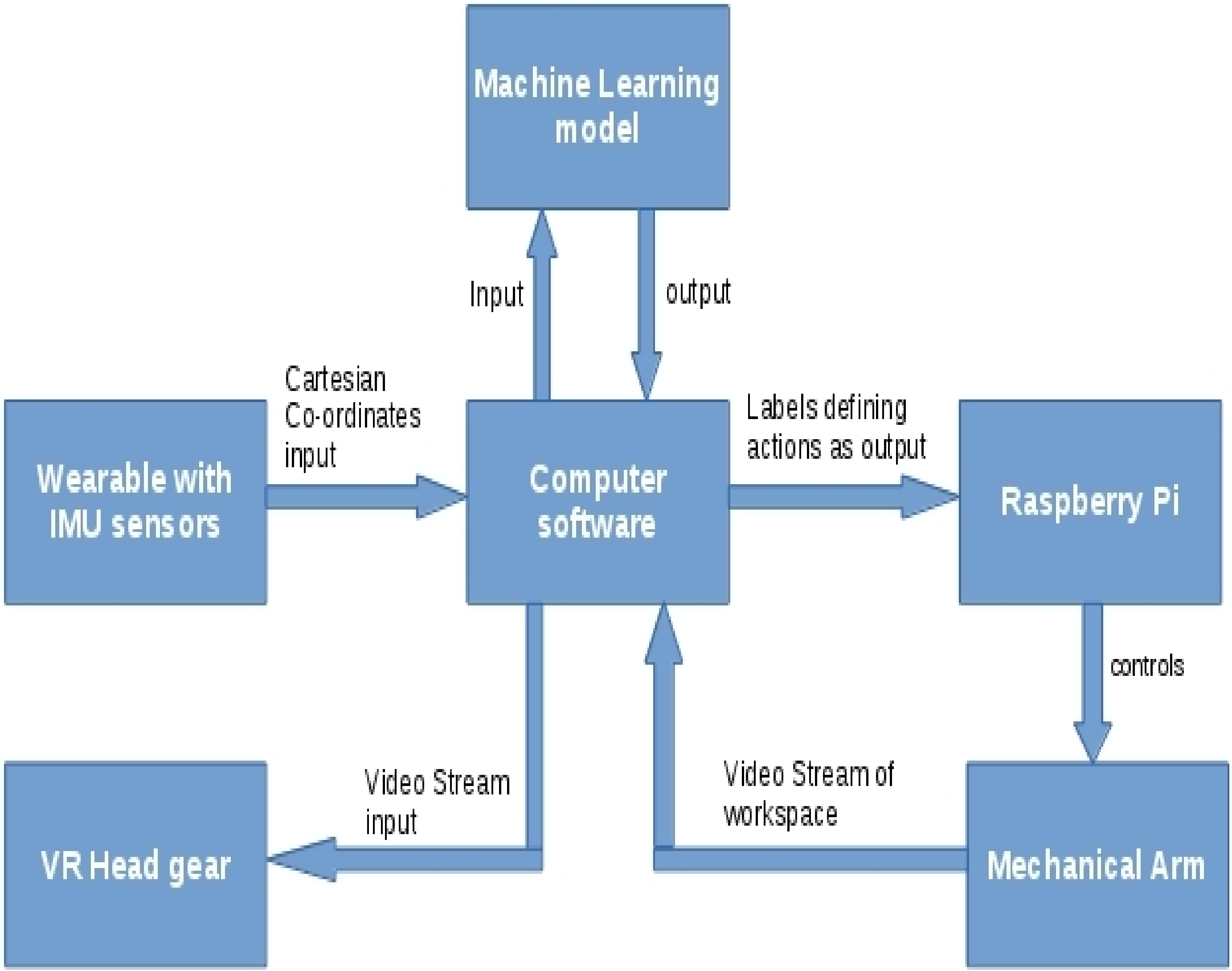
III . PROPOSED SYSTEM

Wearable :

The wearable consists of IMU sensors that get data of yaw, pitch and roll. It also consists a flex sensor that detects the bending of fingers. The communication between the various modules is done using bluetooth. Wearable consists of a bluetooth module HC05 which will help in this communication. The flex sensor of the wearable is able to detecting its bending due to the change in the resistance of its material due to bending. These data is send as input to the machine learning model.

VR Head Gear :

A mobile consisting of VR app will be placed inside the head gear that will stream the live video of the workspace. The VR app works in a split screen format designed using android studio. The app would collect the sensor data i.e the data from accelerometer as well as gyroscope sensor from mobile to capture the orientation. This data will be added as an input to machine learning model to control the servo motors of the platform where camera is kept so that we can move the camera in workspace accordingly.



Linux Application :

The linux application is responsible for running the machine learning model and handling the communication between wearable and mechanical arm. Linux application is made out of PyQT5 which is a Python interface for Qt, one of the most powerful, and popular cross-platform GUI library. The application will be running using bluetooth in background to collect data of sensors from the MPU6050 on wearable and the accelerometer gyroscope sensors from mobile. The continuous real-time data will be given as input to the machine learning model to generate required output for control of mechanical arm.

Machine Learning model :

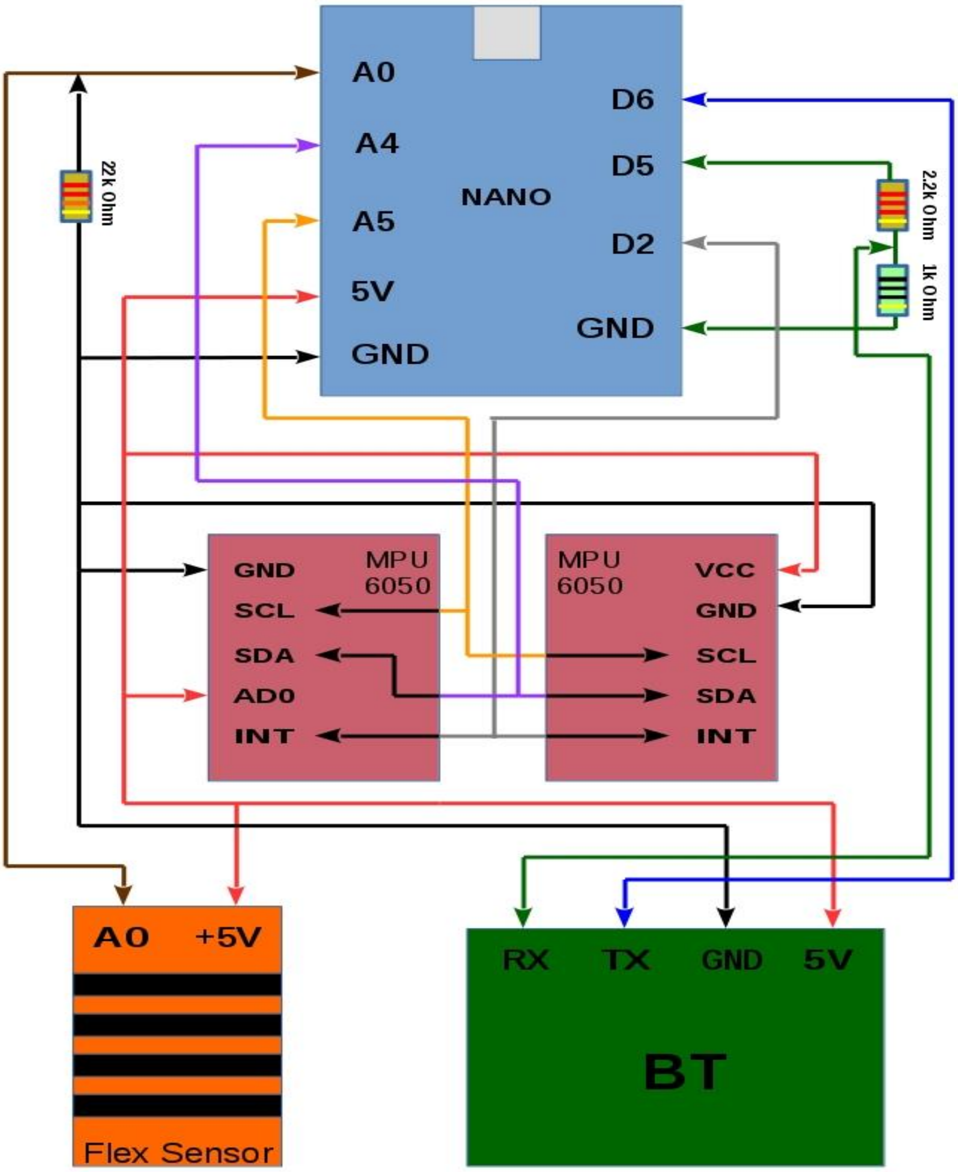
The model gets prepared after learning process using the data acquired from sensors. This machine learning model is used to predict the actions to be performed by the mechanical arm. The output of machine learning model is in the form of labels that are mapped to the type of action performed by mechanical arm. The output labels get mapped to the servo motor rotation angles of mechanical arm and accordingly each joint movement takes place. The algorithm used is Support Vector Machine (SVM) which is proved to be efficient and fast for classification with less number of features as compared to other models.

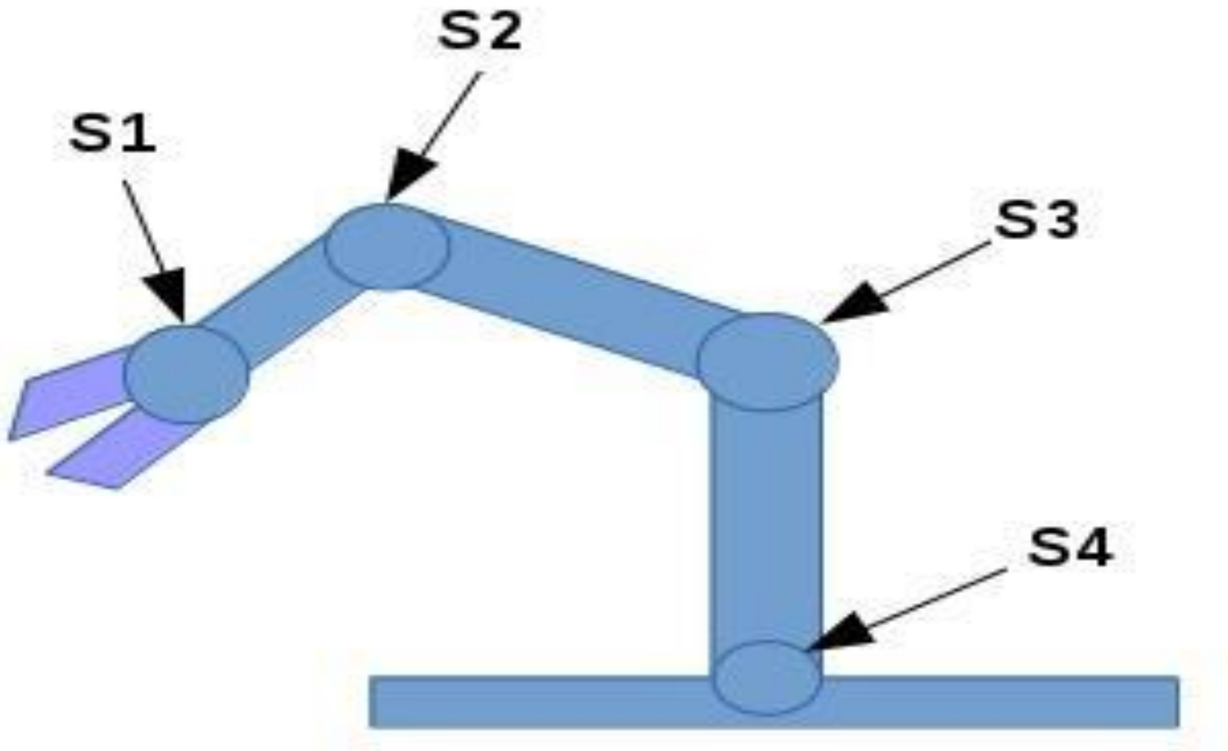
M1-X	M1-Y	M1-Z	M2-X	M2-Y	M2-Z	F

Wearable Glove Output Tuple

Here ,

M1-X = X axis value of IMU sensor 1.
M1-Y = Y axis value of IMU sensor 1.
M1-Z = Z axis value of IMU sensor 1.
M2-X = X axis value of IMU sensor 2.
M2-Y = X axis value of IMU sensor 2.
M2-Z = X axis value of IMU sensor 2.
F = Value of Flex sensor .





Data Collection :

This is an important task which has to be carried out carefully in machine learning model because these are the information that defines the knowledge of machine learning model.

Since large amount of data can cause problem such as overfitting which is not suitable for developing an accurate machine learning model. In the same way less amount of data can cause problem such as underfitting which again is not suitable for developing an accurate machine learning model.

Hence our model needs to have adequate amount of data so that it can develop an accurate machine learning model .The data should cover as many areas of action as possible for the model so it should be versatile. In order to provide the servo motors accurate angels , regression would not be appropriate since there are multiple servo motors to be handled and multiclass regression would not be able to provide appropriate results. Hence multiclass classification would be more appropriate for this kind of system where multiple motors values can be predicted through classification mechanism.

Classification requires selection of labels . Labels defines the corresponding action and the angels of the servo motors which is to be given as output. Selection of labels is an important task which has to be carried out carefully in machine learning model because if we select large number of labels problems such as high amount of computation and overfitting of models might occur. If we select less number of labels then the model would not understand many of the actions to be performed which would result into underfitting of the machine learning classification model.

Hence we carried out carefully the process of selecting number of datasets as well as number of labels for our machine learning classification model. We used python as well Arduino IDE to create serial connections between our program and the equipment.

Our python program was controlling both Arduino nano and Arduino uno . Arduino uno which is mounted on mechanical arm and Arduino nano which is mounted over data collection glove. Putty ssh client provides an easy to use interface which was used to read the serial connection between Arduino and python.

It provides a serial monitoring interface as well as functionalities to save the serial reading in file format and hence makes it easier to handle data collection. We collected data by connecting both mechanical arm Arduino as well as data collection glove in the same pc using different files but common timestamp which was maintained by the pc time as well as python program.

	A	B	C	D	E	F
1	index	s1	s2	s3	s4	label
2	18	999	18	18	999	updown2
3	36	999	36	36	999	updown3
4	54	999	54	50	999	updown4
5	72	999	72	50	999	updown5
6	90	999	90	50	999	updown6
7	108	999	108	50	999	updown7
8	126	999	126	50	999	updown8
9	144	999	144	50	999	updown9
10	162	999	162	50	999	updown10
11	180	999	171	50	999	updown11
12	198	999	153	50	999	updown12
13	216	999	135	50	999	updown13
14	234	999	117	50	999	updown14
15	252	999	99	50	999	updown15
16	270	999	81	50	999	updown16
17	288	999	63	50	999	updown17
18	306	999	45	45	999	updown18
19	324	999	27	27	999	updown19
20	342	999	9	9	999	updown20
21	18	999	18	18	999	updown2
22	36	999	36	36	999	updown3
23	54	999	54	50	999	updown4
24	72	999	72	50	999	updown5
25	90	999	90	50	999	updown6
26	108	999	108	50	999	updown7
27	126	999	126	50	999	updown8
28	144	999	144	50	999	updown9

Data Collected from Mechanical Arm

	A	B	C	D	E	F	G	H	I
1	index	m1x	m1y	m1z	m2x	m2y	m2z	f	label
2	18	2.5	12.89	89.25	-89.92	26.37	-48.68	21	updown2
3	36	-25.49	157.1	117.45	-85.09	25.81	-39.37	20	updown3
4	54	-61.49	-55.51	74.34	-81.84	24.99	-30.62	21	updown4
5	72	-48.6	-55.46	58.84	-78.02	22.48	-22.57	21	updown5
6	90	-43.63	-54.48	45.78	-75.31	20.29	-15.43	22	updown6
7	108	-40.46	-53.08	33.99	-72.9	17.95	-8.3	21	updown7
8	126	-37.41	-49.99	27.66	-71.42	16.27	-4.97	21	updown8
9	144	-33.34	-47.68	21.86	-68.77	15.06	-1.35	21	updown9
10	162	-28.16	-44.54	16.16	-64.84	12.92	1.94	20	updown10
11	180	-26.6	-43.65	11.47	-63.06	12.15	6.18	21	updown11
12	198	-27.55	-43.44	10.91	-63.88	13.04	7.89	20	updown12
13	216	-28.48	-42.99	7.72	-64.32	12.61	10.93	22	updown13
14	234	-29.09	-42.36	5.77	-64.78	12.62	12.91	21	updown14
15	252	-29.86	-41.74	3.67	-65.28	12.31	14.7	22	updown15
16	270	-30.62	-41.19	3.72	-66.03	12.63	15.01	21	updown16
17	288	-29.41	-39.77	2.48	-65.17	11.59	15.83	15	updown17
18	306	-29.72	-38.08	0.79	-65.68	9.98	16.7	21	updown18
19	324	-29.73	-39.11	-1.75	-65.31	10.11	19.66	21	updown19
20	342	-30.35	-37.87	-1.54	-66.23	9.58	19.21	20	updown20
21	18	111.41	-6.76	-41.21	-31.63	179.79	-100.02	13	updown2
22	36	110.28	-8	-36.38	3.34	1.55	-89.51	11	updown3
23	54	109.22	-9.52	-32.12	37.61	2.41	-78.76	11	updown4
24	72	108.8	-10.86	-28.25	56.46	3.67	-68.03	11	updown5
25	90	108.25	-11.82	-25.33	66.57	4.31	-57.49	11	updown6
26	108	107.96	-12.65	-22.76	72.17	4.88	-47.7	11	updown7
27	126	107.92	-13	-20.59	76.15	5.18	-38.76	12	updown8
28	144	107.36	-13.87	-18.85	77.88	5.07	-30.79	12	updown9

Data Collected from Data-Collection-Glove

V. Conclusion

In this paper, we proposed a system for imitation of hand gestures by a mechanical arm which would help operate machines wirelessly from a distance easily so that we can operate machines that are used in hazardous places where . This provides a comfortable work environment for operator and the handling of machines with complex controls can be done easily through hand gestures. For wireless communication Bluetooth and Wi-Fi can be used .We have combined algorithms like SVM and PCA to design an effective machine learning model. This system can be further developed to perform computations over cloud and control machines through Internet if Bluetooth or Wi-Fi connection is not possible.

VI. Acknowledgment

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