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SERIAL REDUNDANT MANIPULATOR CONTROL SCHEME VIA NEURAL NETWORKS: A SURVEY.

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Abstract: Recently robotic manipulators have gained tremendous applications over variety of engineering and science fields. The main agenda of utilizing robotic manipulators is to decrease the human effort and simplify complex operations, like operating via tight narrow channel and inspecting sewage pipes for obstructions. Robot control is one of the fields where substantial research is being carried out focusing on achieving higher levels of autonomy in robot activity. The IK of redundant serial manipulators faces numerous possible constraints, such as singularities, making accurate tracking in complex environments. All these can be overcome by neural networks which possess high control precision and system robustness which are regarded as a reliable tool for instantaneous analysis adopted in numerous control systems. Neural networks are now a popular topic of discussion in manipulator control research, and a variety of related schemes and approaches have been addressed and researched. The purpose of the paper offers a quick survey on recent advances of serial manipulators control using neural networks. Further potential directions on this topic are identified and discussed.

Index Terms **- Redundancy, redundant manipulator, redundancy resolution, neural networks.**

I. INTRODUCTION

In recent years robotics has been a comparably modern field of modern technology that surpasses traditional engineering boundaries (Jin et al., 2018). Robots are being utilized used in rehabilitation (Vitiello et al., 2017), motion assistance (Alonso-Mora et al., 2018), cognition (Srinivasan, 2021) and target detection and tracking (Zheng et al., 2019) in addition to space (Aghili, 2020) and numerous other industrial applications (Kaczmarek et al., 2021) on a regular basis. They are actively employed to accomplish tasks having strict requirements of repeatability, precision, accuracy, mass production and quality to ease of human effort. Ideal example applications of robots in industry include packaging, arranging, moving, welding, paint spraying, sanding, and cutting. A tremendous amount of research has been contributed to robotics, especially in the creation and investigation of various types of robot manipulators such as serial manipulators like redundant manipulators (Bi et al., 2017) and mobile manipulators (Yang et al., 2019), parallel manipulators (Furqan et al., 2017) like cable-driven manipulators (Hong et al., 2018) as shown in Fig1(a), (b), (c) and (d).

Figure 1(a). Serial manipulator

Figure 1(b). Parallel manipulator

Figure 1(c). Mobile Manipulator

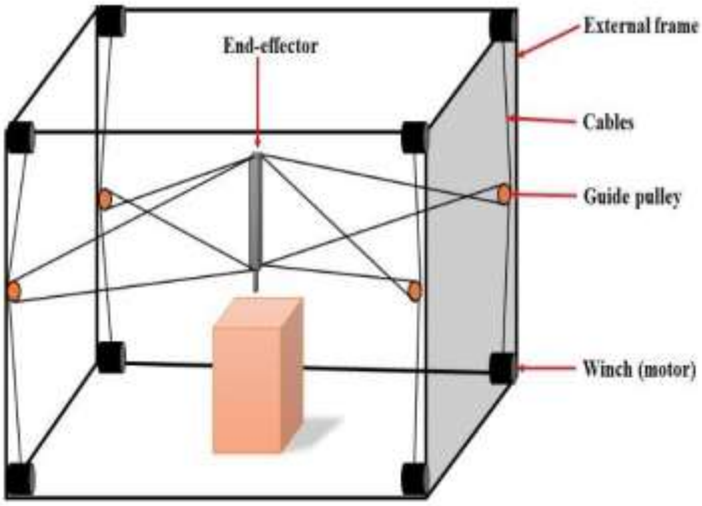

Figure 1(d). Cable-driven manipulator

Serial manipulators consist of sets of links that stretch from a base to end -effectors actuated by motors in the link's joints. Any type of manipulator, either serial or parallel, are redundant in nature when it possesses more than 6 degrees of freedom (DOF) than its requirement for implementing a given task (Z. Zhang & Zhang, 2013). A robotic design which consists of a movable platform and a redundant manipulator attached on the surface of the mobile dock is referred as mobile manipulators (Yang et al., 2019). The following is the generalized structure of the paper: Following the overview, Section 2 presents preliminary information about the kinematic and dynamic modelling including the error formulation of a robot manipulators. Section 3 provides overview of redundant manipulators followed by Section 4 further focuses on how various neural networks can be used to control robot manipulators. In addition, Section 5 reflects two potential future research avenues for controlling robot manipulators using neural networks. Section 6 brings the paper to an end with some closing remarks.

II. OVERVIEW OF REDUNDANT MANIPULATORS

Redundant manipulators are more versatile as they possess a greater number of degrees of freedom that are critical to interpret a process (Z. Xu et al., 2019b) as shown in Fig 2. As a result, they are extensively used in manufacturing and space exploration due to their fault tolerant performance, reliability, and greater efficiency. Typically, redundancy solution is employed to gain a certain goal, like avoiding singularities, barriers and so on. On the other hand, force control requires a robot's physical contact with its surroundings as the redundancy are deemed to be a major aspect for carrying out tasks that requires a level of capability in comparison to a human arm, including in outer space industry applications like the SPDM (Aghili, 2020), a crucial element of the Canadarm2: Robotic Arm which was modelled by Canada in use for the International Space Station, considerable emphasis has been devoted to the research of these manipulators in recent years (Urrea & Kern, 2012).

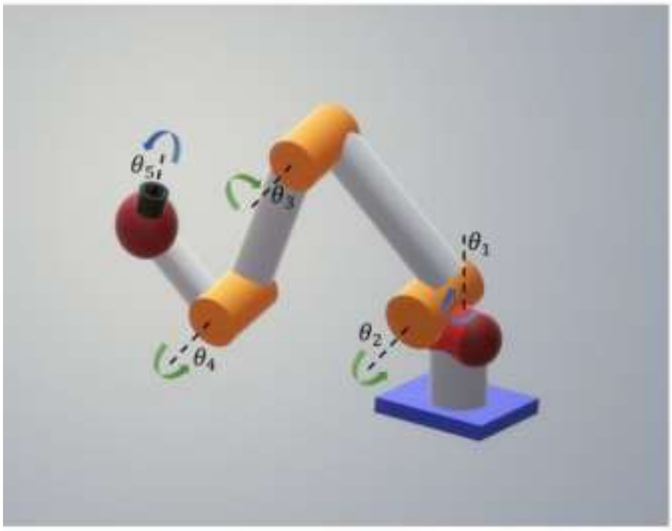

Figure 2. Basic structure of redundant manipulator

Although most non-redundant manipulators own an adequate amount of DOF to accomplish the primary duties, such as orientation and position mapping, it is well established for the limited manipulability which shortens the workspace caused by mechanical constraints of the joints along with the existence of objects in this room. This drawback has encouraged many academics to investigate how the manipulators behave when they are more DOF (kinematic redundancy) introduced, allowing such devices handling more tasks determined by the end-user. These activities could be interpreted as kinematic functions and can include dynamic yield data as well as kinematic functions that indicate favorable features of the manipulator's behavior, such as joint characteristics and obstacle avoidance (Z. Xu et al., 2019c). By specifying functions such as impact force, inertia control, and so on in the robot's dynamic model.

III. MANIPULATOR CONTROL USING NEURAL NETWORK

The prior section has described about basic control techniques predominately used for serial manipulator control. This section begins with a description of neural networks algorithms applied to manipulator control problems from a new viewpoint. The redundancy control-based on neural network for manipulators have been an interesting topic for numerous articles. The aim of this research is to lower the computational complexity of manipulator along with motion planning and control via neural network. It can be used to learn manipulator's control that do not have a well-defined layout. The input, hidden, and output layers are the three

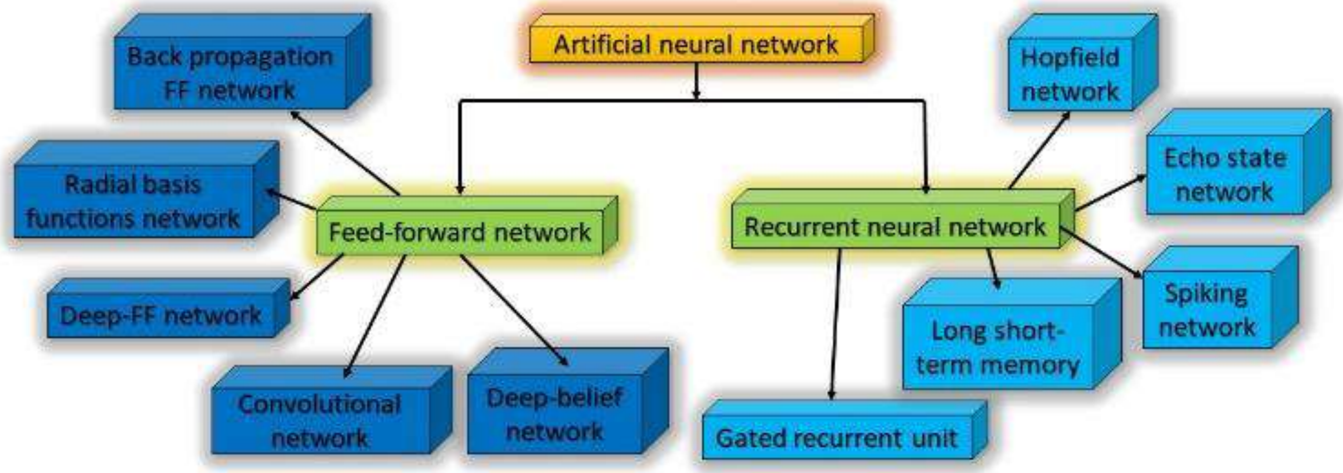

Figure 3. Classification of neural network

layers of an ANN, as shown in Fig 4, and they differ depending on the architecture framework type (Zou et al., 2006) as shown in Fig 3. The ultimate goal of ANN is to instruct a series of parameters (weights) that can represent the mapping between user-inputs and data sent to manipulators (Hasan et al., 2010b). In the manipulator controlling task, there are two major forms of neural network training algorithms: off-line training and on-line training. Offline learning is most widely used in industries for controlling manipulators for different operations since the model can only be programmed with the data given to it and simulate a certain form of data. Online training, on the other hand, is a method of ingesting a sample of real-time data one observation at a time. These algorithms can only process one set of data at a time, giving them a time and space advantage (Kaczmarek et al., 2021). It is easier to train an off-line network since the parameters of the constructed neural network are not changed as it is applied to corresponding manipulators.

4.1. Feed-forward neural networks

This type of network is one in which the connections between nodes do not form a loop. It was the first and most basic neural network to be developed and information over here flows only in one direction: by the input point to the target point, via some hidden layers (Jin et al., 2018). Feed-forward neural networks can also be used for classification and decision-making in a variety of engineering and scientific issues, including connection, robotics, regulation, pattern recognition, perception, and many other disciplines that have yet to be investigated26. Fig 4 and 5 illustrates the basic structure and workflow of an FNN.

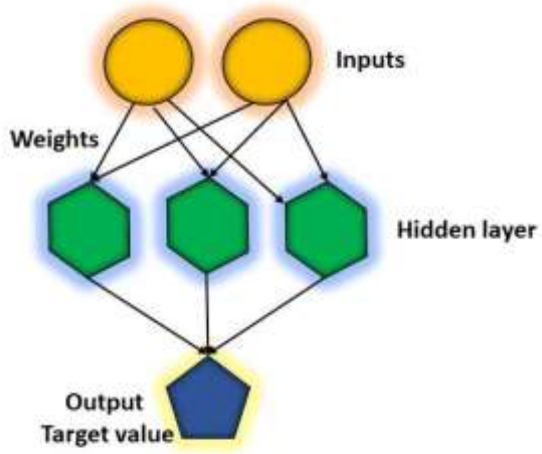

Figure 4. Workflow of a neural network

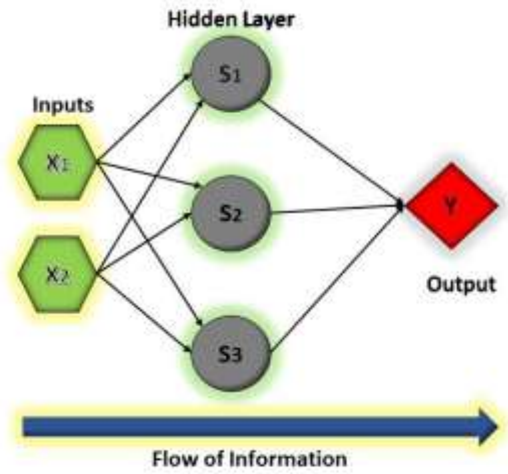

Figure 5. Feed-forward neural network

4.2. Recurrent network

Information within a RNN can flow in both directions, meaning it can flow from one node to the next or form a closed cycle within a single node as shown in Fig 7. It has also shown to be the most effective method for regulating serial manipulators. In (Li et al., 2017) an RNN-based controller was used to solve two problems: (1) optimizing control precisions and (2) the robot motion adaptability. It was chosen primarily because the problem formulation naturally corresponds to the RNN structure, and it has the advantage of being a biologically based procedure; for this reason, they used the Raven II surgical robot to implement the proposed method.

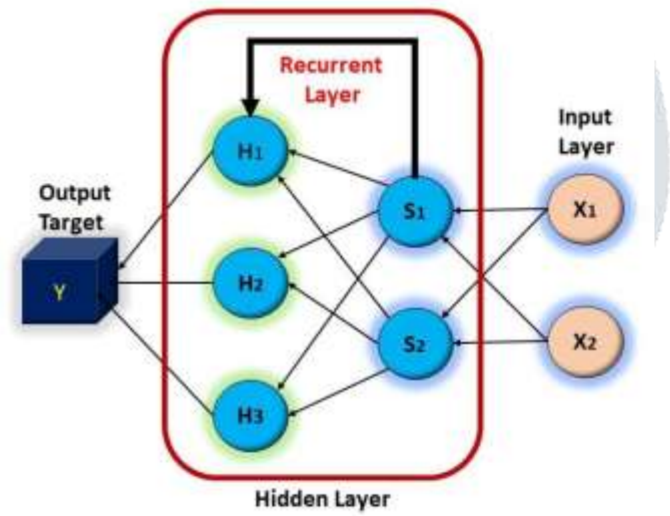

Figure 7. Recurrent neural network

Visual servoing is the use of an eye-in-hand camera to control the kinematics of a manipulator. A recurrent neural network is used to solve the visual servoing issue, which is described as a constrained optimization problem (Y. Zhang et al., 2017).

4.2.1. Hopfield network

They utilized HNN to carry out coordination among the agents based on the distinct actuation output without understanding it beforehand, and they applied an algorithm for the energy-efficient coverage optimum control method in (Turanli & Temeltas, 2020a).(Atencia et al., 2004) proposes an online recognition approach for non-linear structures based on Hopfield network.

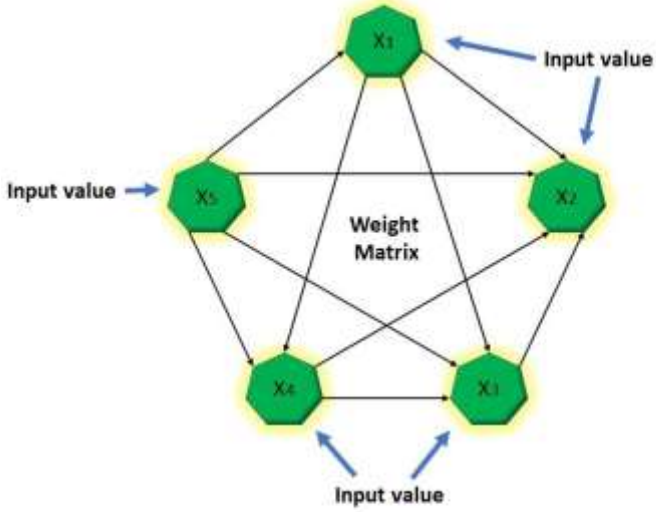

Figure 8. A 5-node neuron Hopfield network

In case of time-varying parameters and constant parameters, the convergence to a limited neighborhood is efficient.
A robotic unit with a versatile connection is identified using the proposed approach. The online parameter estimation with Hopfield networks for a robotic device is suggested in (Alonso et al., 2009) along with the findings of the stability and robustness study are experimentally confirmed. As suggested in the Hopfield Neural Network is an online parameter estimation methodology used to predict actuator output parameters, shown in Fig 8.

4.2.2. Spiking neural network

SNN has a structure more like to that of a biological neuron as compared to the earlier networks. The input and output parameters are frequently depicted as "spikes," indicating a delta function. The capacity of a SNN is to accommodate spikes varying in time, as illustrated in Fig 9, is one feature that should be highlighted. In (Rusu et al., 2017; Turanli & Temeltas, 2020b), to enable rapid modelling of the large-scale networks for control utilizing SNN, a paradigm known as "Robby" was developed. It comes with tools for building and modelling neural controllers, as well as a communication framework for robots.

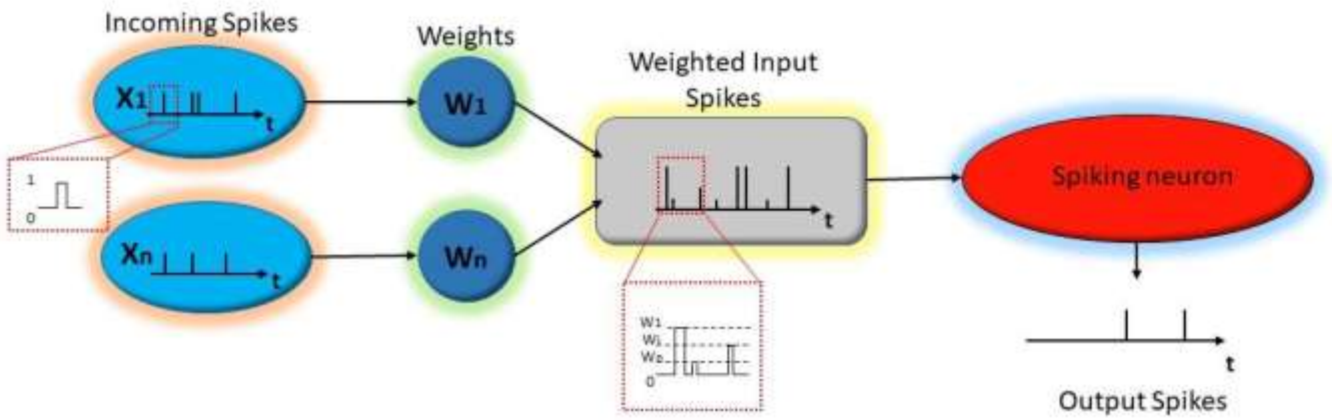

Figure 9. Spiking neural network

4.2.3. Echo state network

The fundamental concept behind this network is to use an erratically generated reservoir to substitute the hidden layer in a standard network. To create an ESN, we must first create a reservoir with random connections. The size of the reservoir and the number of neurons inside it can be determined by the size of the problem to be solved. The dotted line represents the weights from the reservoir to the output neuron in Fig 10, these are sole parameters influenced by the learning mechanism. The output layer to the reservoir can be used to form a closed loop. In (Yingjie Deng, 2021), ESN was used to provide for uncertain dynamics in the model of autonomous surface vessel tracking control (ASVs). The MBETC system is provided as a combination of ESN training and compound disruption computation utilizing the compound training approach.

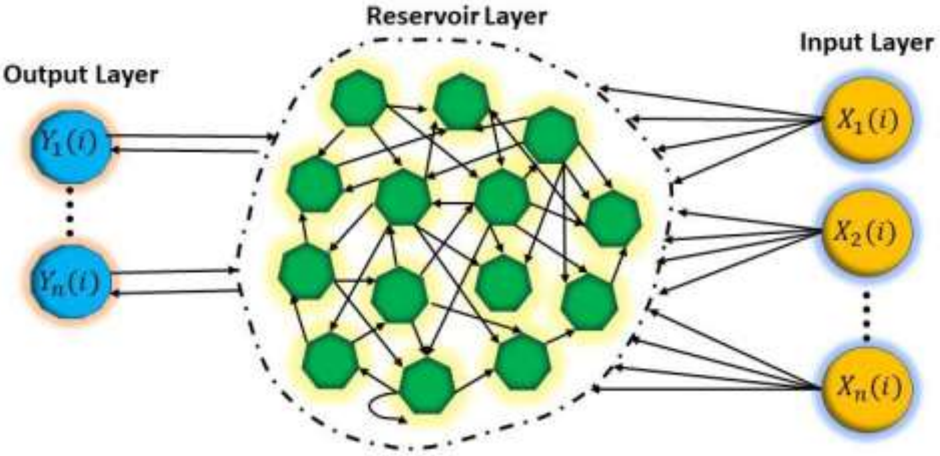

Figure 10. Echo state neuron network model

While computing weights in this network is straightforward, the reservoir's complexity tends to rise as the challenge grows. The ESN is a kind of ARNN made up of randomized and non-trainable weights that function as a repository for external stimulation, producing a vast range of dynamical echoes, and a linear combo of those echoes created by the output layer.

4.3. Deep neural network

This network consists of more than two layers that has a certain amount of complexity and processes data in diverse ways using advanced mathematical modelling. Deep neural networks, according to many researchers, are networks with an output layer, an input layer, and one unknown layer in between (Nguyen & La, 2019) illustrated in Fig 11. In a method known as "function hierarchy," each layer performs various methods of sorting and ordering. Dealing with unlabeled or unstructured data is the at most important applications from these advanced neural networks. The ability to realize the kinematic chains for a randomly positioned group of sensors were presented in (Salman et al., 2018) by training a deep network of linear and nonlinear layers over a range of serial manipulators.

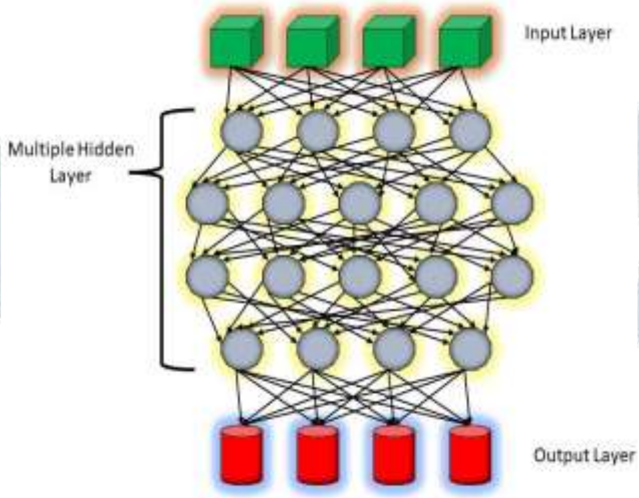

Figure 11. Deep network architecture

4.3.1. Convolutional neural network

CNN are the majorly comprehensive paradigm for using deep learning to solve machine vision problems (Nguyen & La, 2019). An article here describes about a resolute control scheme for acceleration control-based on deep CNN regression in (Linsley et al., 2018) which were identified by a CNN with a framework style DAG network (or DAG-CNN) as shown in Fig 12, which achieves an accuracy of 84.5 % in gesture recognition. Similarly, real-time experiments are carried out on the already qualified network, in which the user is in a semi-controlled environment indicating the various activities for the robot to execute, and the proper operation of the trained network is tested, resulting in a high precision in command recognition and no errors in the robot's control actions.

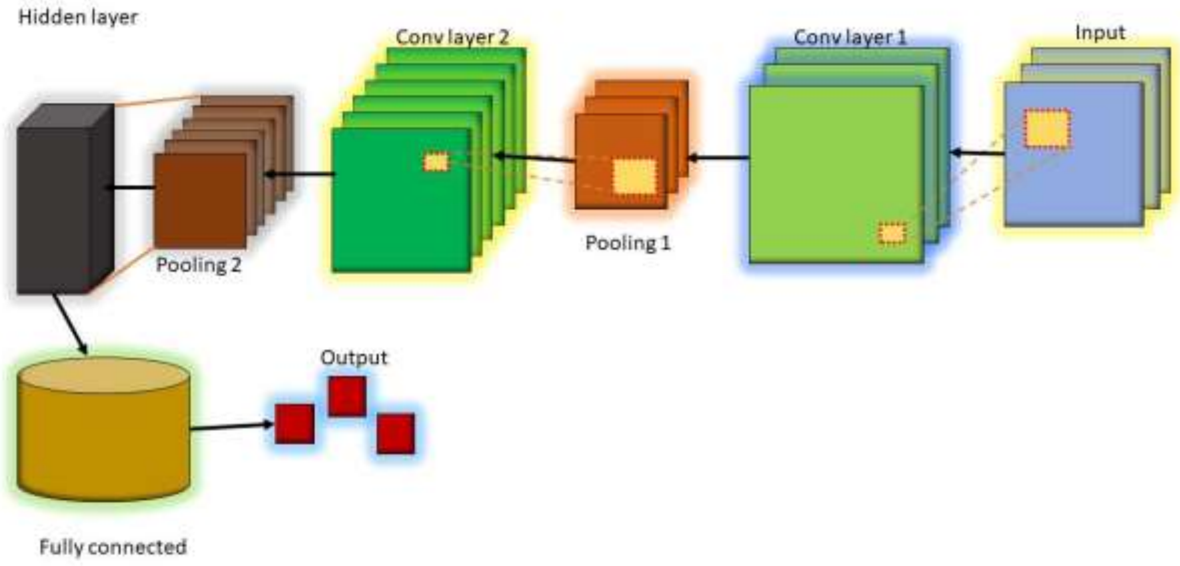

Figure 12. Convolutional neural network architecture

IV. FUTURE SCOPE

According to the papers and articles referred, control schemes have evolved periodically regarding the criteria and responsibilities assigned to them. Further studies focused on this research will concentrate on more complex manipulator motions and addressing redundancy parameters of redundant manipulators in very confined environments, small spaces, and narrow channels, conducting operations such as checking drainage pipelines for blockages and even large search and rescue missions. If we look deeper there are two techniques to be experimented in future which can be used for control mechanism to operate in such confined spaces. One is Winner-take-all control and another concept whitening which is recently being implemented in interpretable image recognition.

V. CONCLUSION

Control strategies have enhanced the manipulator's functionality and reliability dramatically across time. The control technique choice and the implementation manner will have a significant effect on a manipulator's performance and correspondingly with its application scope. In the last two decades, substantial progress has been made in manipulator control using neural networks. But nevertheless, there are already a bunch of new setbacks to be resolved. Considering various types of neural networks have varied potential sets as shown in Table 1, it's impossible to expect only few current data to address all the complications in the control that emerge in diverse manipulators with varying job requirements. Many papers had been explored to achieve this aim, particularly in the areas of control schemes and redundancy resolutions via neural networks.

VI. ACKNOWLEDGMENT

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VII. DECLARATION OF INTEREST

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

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