Metaverse in InterPlanet Internet: Navigating Resource Space with Deep Neural Networks and Functional AI for Predicting Material Surfaces

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ABSTRACT

The interplanet internet is a conceived computer network in space, consisting of a set of network nodes that can communicate with each other. These nodes are the planet's orbiters (satellites) and landers (e.g. robots, autonomous machines, etc.) and the earth ground stations, and the data can be routed through Earth's internal internet. As resource depletion on Earth becomes real, the idea of extracting valuable elements from asteroids or using space-based resources to build space habitats becomes more attractive, one of the key technologies for harvesting resources is robotic space mining(minerals, metals, etc.,) or robotic building of space settlement. The metaverse is essentially a simulated digital environment mimicking the real world. The metaverse would be something very similar to real world planetary activities where users(space colonies or internet users on Earth) interact with overlaying objects represented by robots, drones, etc. for real-world planetary activities like space mining, building space settlements, etc. in a completely virtual manner. Here we show how prediction of space resources may be improved by capturing resource structures from a material sequence i.e. the material/metals character concealed within resource sequences. With this background, the neural network based on simplified version of GAN(Generative Adversarial Networks) is deployed, that get finely tuned during training, in this case to predict concealed residual structures and it is discovered that when the network is well-trained to predict the masked patterns of natural resource sequences, then its internal weights are actually capturing, or "understanding", resource structure. The Information about the structure being modelled develops within the network, and the resource structure is predicted from the patterns activated inside the network. The desired response or generator loss, was defined as the yield of the target product, and new conditions and patterns were synergistically combined with automation in Space Robot and may lead to improved yield when

graphically interpreted. The results of the study simulated on existing internet here on Earth show that the real individual behaviour on a distant planet can be achieved provided the interplanet internet is available as pathway communication. Therefore, connected metaverse with different encoded layers of virtual spaces for tracking resources along with deep learning models with structural patterns could be of reality even in interplanet environment.

INTRODUCTION

Inter-planetary exploration, be it Lunar habitation, asteroid mining, Mars colonization or planetary science/mapping missions of the solar system, will increase demands for inter-planetary communications. The movement of people and material throughout the solar system will create the economic necessity for an information highway to move data throughout the solar system in support of inter-planetary exploration and exploitation. The communication capabilities of this interplanet information highway need to be designed to offer; 1) continuous data, 2) reliable communications, 3) high bandwidth and 4) accommodate data, voice and video.

The interplanetary Internet is a conceived computer network in space, consisting of a set of network nodes that can communicate with each other. These nodes are the planet's orbiters (satellites) and landers (e.g., robots), and the earth ground stations. For example, the orbiters collect the scientific data from the Landers on Mars through near-Mars communication links, transmit the data to Earth through direct links from the Mars orbiters to the Earth ground stations, and finally the data can be routed through Earth's internal internet. Interplanetary communication is greatly delayed by interplanetary distances, so a new set of protocols and technology that are tolerant to large delays and errors are required. The interplanetary Internet is a store and forward network of internets that is often disconnected, has a wireless backbone fraught with error-prone links and delays ranging from tens of minutes to even hours, even when there is a connection. In the core implementation of Interplanetary Internet, satellites orbiting a planet communicate to other planet's satellites. Simultaneously, these planets revolve around the Sun with long distances, and thus many challenges face the communications. The reasons and the resultant challenges are: The interplanetary communication is greatly delayed due to the interplanet distances and the motion of the planets. The interplanetary communication also suspends due to the solar conjunction, when the sun's radiation hinders the direct communication between the planets. As such, the communication characterizes lossy links and intermittent link connectivity.

The graph of participating nodes in a specific planet to a specific planet communication, keeps changing over time, due to the constant motion. The routes of the planet-to-planet communication are planned and scheduled rather than being fluctuating. The Interplanetary Internet design must address these challenges to operate successfully and achieve good communication with other planets.

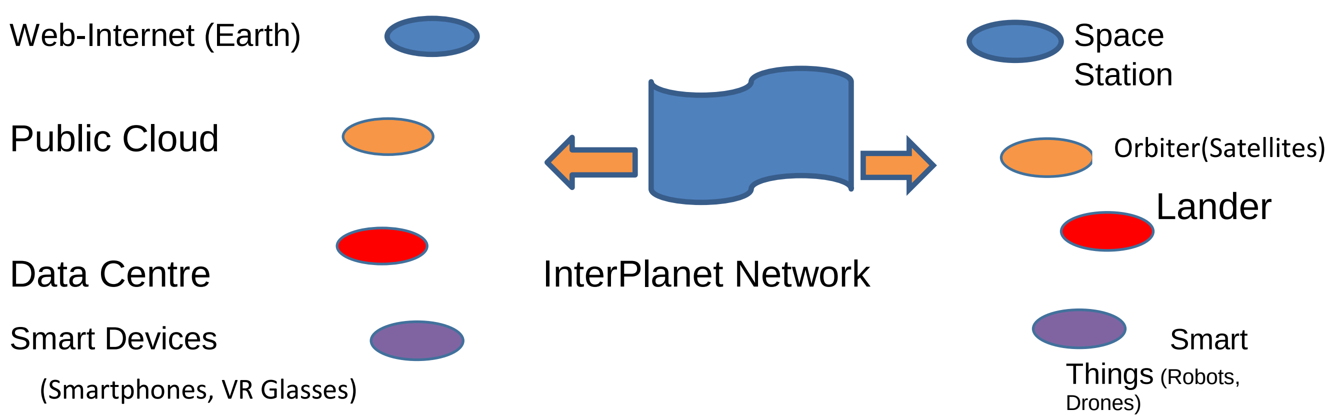
NETWORK ARCHITECTURE

A **Computer Network Architecture** is a design in which all computers in a computer network are organized. An architecture defines how the computers should get connected to get the maximum advantages of a computer network such as better response time, security, scalability, etc.

Network architecture refers to the way network devices and services are structured to serve the connectivity needs of client devices.

- Network devices typically include switches and routers.
- Types of services include DHCP and DNS.
- Client devices comprise end-user devices, servers, and smart things.

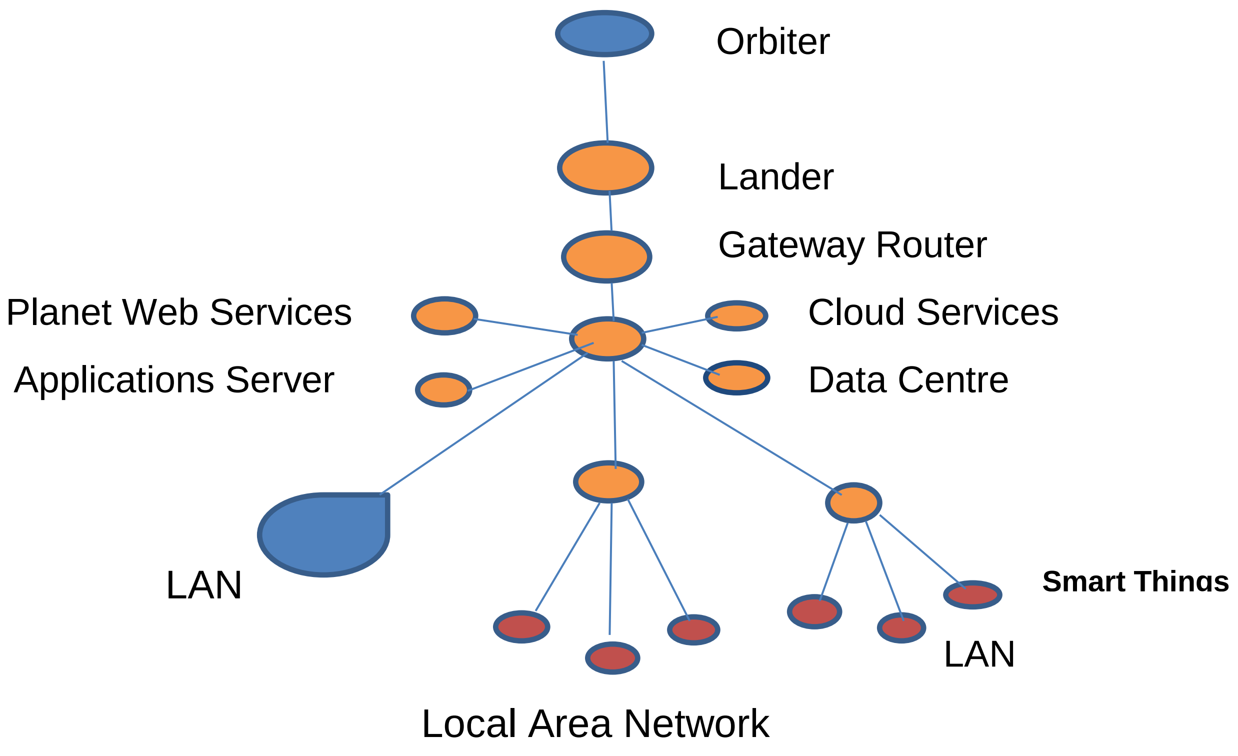
The network architecture for the planet Mars or the Moon is as shown in below figure:-



Computer networks are built to serve the needs of certain functionality and also their clients. Described below are three types of planetary networks:

- Access networks, for campuses and local areas, are built to bring machines and things onboard, such as connecting robots, drones, etc. within a location.
- Networks for data center connect servers that host data and applications and make them available to smart devices.
- Wide-area networks (WANs) connect robots and others to applications, sometimes over long distances, such as connecting robots to cloud applications related to space mining operations.

We give below the architecture of network on the planet Mars or the Earth's Moon is as shown in below figure:-



An Internet is a "network of networks" in which routers move data among a multiplicity of networks with multiple admin. domains.

The main aim of networks is to connect remote endpoints with end-to-end principle and network should provide only those services that cannot be provided effectively by endpoints.

Since the networks are predominantly wireless, the fundamental impact of distance due to speed-of-light delays and impact on interactive applications – for both data and control is to be considered. Also power consumption of wireless links as a function of distance is to be examined.

The interplanetary internet is a conceived networks of nodes and these nodes are space station, planet's orbiters (satellites), planet's landers, robots (drones, autonomous machines, etc.), earth ground stations and earth's internal internet.

METHODOLOGY

Outer space contains a vast amount of resources that offer virtually unlimited wealth to the humans that can access and use them for commercial purposes. One of the key technologies for harvesting these resources is robotic mining of minerals, metals, etc. The harsh environment and vast distances create challenges that are handled best by robotic machines working in collaboration with human explorers. Humans will visit outposts and mining camps as required for exploration, and scientific research, but a continuous presence is most likely to be provided by robotic mining machines that are remotely controlled by humans either from Earth or from local space habitat.

Future **Moon(or Mars)** bases will likely be constructed using resources mined from the surface of the Moon/Mars. The difficulty of maintaining a human workforce on the Moon(or Mars) and communications lag with Earth means that mining will need to be conducted using **collaborative robots** with a high degree of autonomy. Therefore, the utility of autonomous collaborative robotics(with thousands of robots in operation) towards addressing several major challenges in autonomous mining in the lunar(Martian) environment with lack of satellite communication systems, navigation in hazardous terrain, and delicate robot interactions to achieve effective collaboration between robots and long-lasting operation.

Collaborative Robotics

Robots can be shaped to perform specific tasks. Robots have been designed and shaped in such a way that they can walk, swim, push pellets, carry payloads, carry shoveling and work together in a group to aggregate debris scattered along the surface into neat piles or possibly, to build a space settlement. They can survive for long-time without recharge and heal themselves after any damage/confusion. The shape of a robot's body, and its distribution of legs and structure are automatically designed in simulation to perform a specific task, using a process of trial and error.

The methodology is essentially fundamental for getting the space robots as autonomous as possible and the aim is to represent surroundings and their markings from robot in space. Therefore, we use feature extraction from the environment to update the position of the robot. Landmarks are the features that can easily be observed and distinguished from the environment and these are used to localize the robot.

The methodology primarily consists of following parts:-

1. Selecting and deciding on the landmarks (Materials, location, etc.).
2. Extracting landmarks from input of robot sensors/cameras at each time step.
3. Based on time step, get the current position of the robot on the basis of landmark data.
4. Carryout landmark data association with the location of the robot by matching with the landmarks data in the database.
5. Introducing learning agent in the robot that uses deep neural network with learning algorithm
6. The neural network used by the learning agent will be trained with learning algorithm by using different methods
7. Measuring the outcome with generator loss or optimization steps

ARCHITECTURE

1. Augmented Reality

The word ‘augmented’ means to add. Augmented reality uses different tools to make the real and existing environment better and provides an improved version of reality.

As Augmented Reality (AR) technologies improve, we are starting to see use cases and these include product visualization. There are AR apps that allow a customer to place virtual furniture in their house before buying and it is also a powerful tool for marketing as it allows users to try products before buying.

At its core, AR is driven by advanced computer vision algorithms that compares visual features between camera frames in order to map and track the environment. **But we can do more.** By layering machine learning systems on top of the core AR tech, the range of possible use cases can be expanded greatly.

Augmented Reality(AR) can be defined as a system that incorporates three basic features: a combination of real and virtual worlds, real-time interaction, and accurate 3D registration of virtual and real objects

2. Camera Representation

A camera is a device that converts the 3D world into a 2D image. A camera plays a very important role in capturing three-dimensional images and storing them in two-dimensional images. And the following equation can represent the camera.

$$x=PX$$

Here x denotes 2-D image point, P denotes camera matrix and X denotes 3-D world point.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

The above is vector representation of x=PX [1].

The camera representation method is frequently used in image processing and is intended to identify the geometric characteristics of the image creation process. This is a vital step to perform in many computer vision applications, especially when metric information on the scene is needed.

3. *Metaverse Algorithm*

1. **Physical Reality Modeling -** required information
   - The goal of the agent/robot
   - What the robot sees, Materials & location
   - Real Simulation for Task Execution
2. **Task Execution (Simulation)**
   - Generating actual materials(how materials arrive at the site)
   - Robots arrive in the environment (speed and goal)

- Task Execution(Simulation Steps), is updated as the work process progresses in line with the simulation
- Task execution performance, as we have fully functional simulator and to make a realistic system, we would like to see how well it performs and mirrors real world execution(Artificial Intelligence)
- Implementation of Graphical Version of the Task Execution

Models for Metaverse & Algorithm

Minimum amount of required information

- The current state of the robot/agent and its environment
- The goal of the agent/robot
- What the agent sees, materials & it's location

Agents – Attributes

We opt for the agents and they have the attributes: the sight and the goal. While the goal is chosen randomly when an agent arrives on the location, the sight is always fixed to the some value. The other noticeable fact is that our learning agents do not have a desired speed. We define the autonomous robots as entities whose primary concern is to avoid failure; they should consequently not exhibit any preference for a certain speed as long as they are working safely. Furthermore, we add an attribute to these learning agents; this is their probability of choosing a random action at each time step.

Agents as workmen

Given that we define learning agents the same way as the type of workers, we can seamlessly add them at the location. The only difference is how they will choose an action: by using their learning model, a neural network. We can therefore adapt the site's time step's algorithm to take the learning agent into account for the observation step. To decide what action it should take, the learning agent uses a neural network to approximate the Q-function. Thus, at every time step t, the agent c observes its state $s_{c,t}$; this state is then processed in some way so that it can be passed to a neural network whose outputs correspond to all the possible actions. The values of these outputs are the estimated Q-values, Q($s_{c,t}$, a); as it is using a neural network θ, we denote the Q-function approximated with that network by Q(s,t;θ). The agent then uses an ϵ-greedy strategy to choose the action $a_{c,t}$.
The neural network used by the learning agent will be trained with

learning algorithm by using different methods.

Neural Network Models

Presently different neural network models are available that we will use to train our autonomous robots. These models define what information the learning agents use and how they are encoded as inputs to the neural networks. Before we start with our model, we need to define the building structure; how these neural networks are used by the learning agents. We use a feedforward neural network whose outputs correspond to the possible actions. Our models define different ways of using information about the agent's current state. Thus, they either encode different information or encode the same information differently to produce the inputs.

Required Information

We start by defining the minimum amount of information that an autonomous robot should have. Consequently, the model that we design will possess these pieces of information. They are:

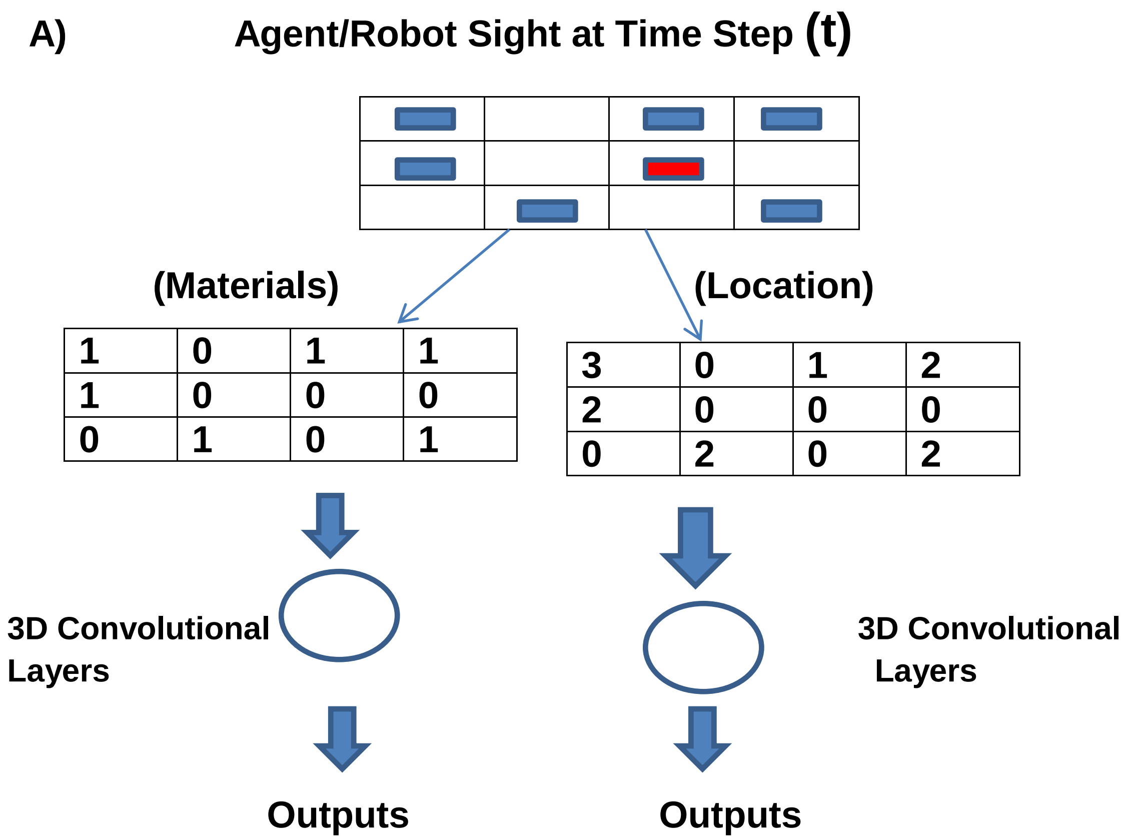
- The goal of the agent/robot
- What the robot sees, Materials & location
- The current location that the agent is in
- The current speed of the agent
- Real Simulation for Task Execution

Task Execution (Simulation)

- Generating actual materials(how materials arrive at the site)
- Robots arrive in the environment (speed and goal)
- Task Execution(Simulation Steps), is updated as the work process progresses in line with the simulation
- Task execution performance and to make a realistic system, we would like to see how well it performs and mirrors real world execution(Artificial Intelligence with learning algorithm)
- Implementation of Graphical Version of the Task Execution

Reddy's Encoding Model

The model is based on the idea as the robot presence at different time steps; we use information about the previous time step (the robots' presence represented by the observation matrix O). This time, the observation matrix of the previous time step $t-1$, denoted O_{t-1}, is not additional inputs, but it forms, along with the current observation matrix, a 3-dimensional matrix with time as the third dimension. We then pass this matrix through a 3-dimensional convolutional neural network . We also keep decreasing the number of inputs by including the learning agent itself in its observation matrix. Figure 1 illustrates this model that we call reddy's encoding model of time-step, as it encodes the robots' presence at different time steps. The learning agent is shown in red while materials in its field of view are in blue. All the input vectors are concatenated and passed to the network.



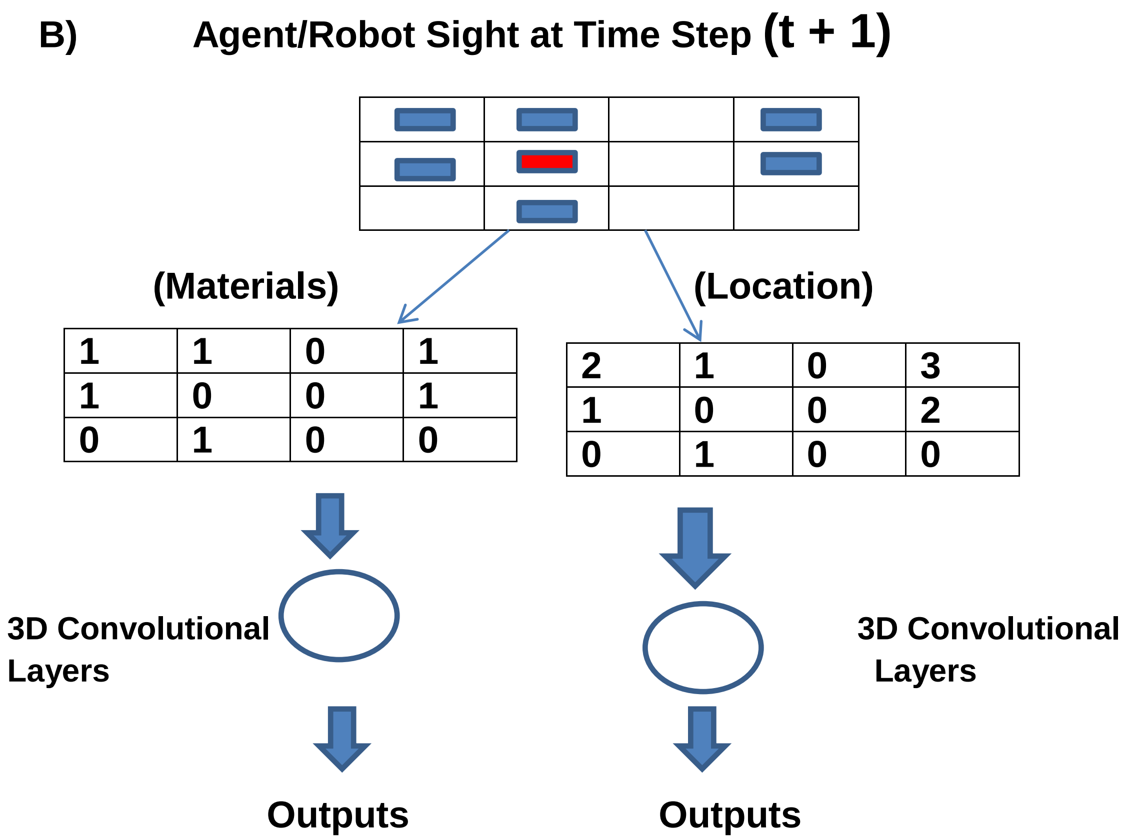


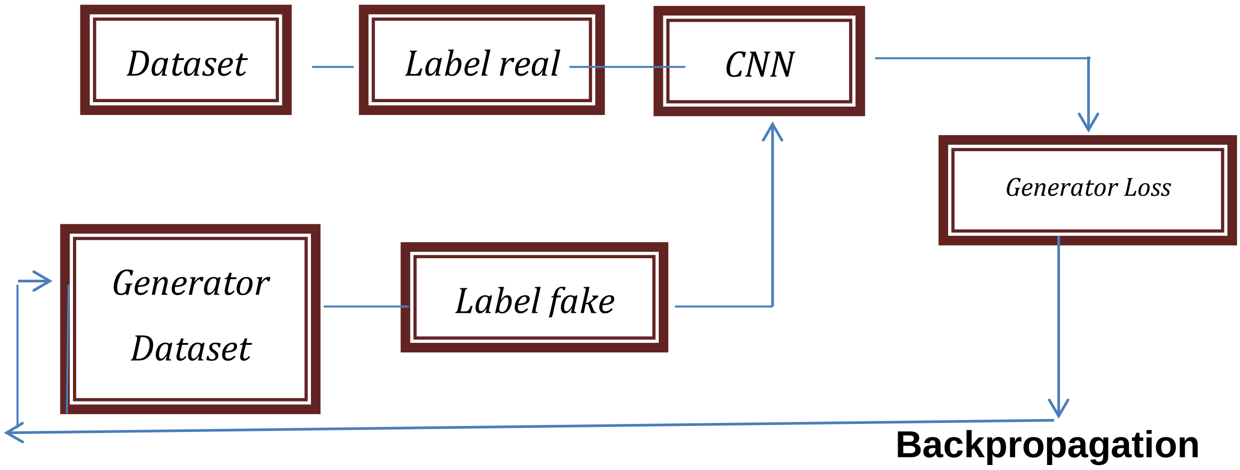
Fig 1. Model encoding of an agent/robot with a goal.

Our first step is the basic information regarding the robot vision and it's location. We define the model with each input as either 0 or 1 and information regarding the field of view of the agent/robot can only be 1 if there is something , or 0 if there is nothing. The agent/robot only knows whether there is a material to be used in some position and its location with respect to materials identified.

We have represented this model as matrix with encoded values with possible values for each of these attributes.

Material Structures Prediction

We have used slightly different & simplified version of GAN(Generative Adversarial Network) and the following steps are executed back and forth allowing simplified GAN to tackle otherwise difficult generative related predictive problems.



1. Select real images from the training data set
2. Generate a number of fake images(in reality the images are related to synthesized structure of natural resources or other materials) using the generator
3. Train the network(CNN) for one or more epochs using the real images
4. Train the network(CNN) model for one or more epochs using only fake images
5. Compare with real images by calculating the generator loss
6. Finally the backpropagation is performed on the Generator of input images. Here the network weights are not updated but only the generator is tuned to make it to learn the real requirement.

RESULT

Convolutional Neural Network (CNN) functional model was used for the image processing as it uses multilayer perceptions, and we have used MNIST dataset(dataset of handwritten images) in absence of any real data on planetary natural resources and their structure.

For this task, the system with different layer configurations for the hidden structures of the networks is as below:

- 2 hidden layers: the first with 28 neurons and a *tanh* activation function; the second with 10 neurons and a *linear* activation function. Dropout rate of 0.5.

We calculated the generator loss, then backpropagation to reduce the loss and to improve the prediction accuracy.

CONCLUSION

The interplanetary computer network in space is a set of computer nodes that can communicate with each other. We proposed a network architecture with planet's orbiters, landers (robots, etc.), as well as the earth ground stations and linked through Earth's internal internet, and consisted of complex information routing through relay satellites to address direct planet-to-planet communication. As we know, the metaverse will be very different from the internet of today due to massive parallelism, three-dimensional (3D) virtual space and multiple real-world spaces like space mining, building space habitats, etc. Here we have shown how resource synthesis may be improved by capturing material structures from a resource sequence and specifically to predict the material character concealed within resource sequences. With this background, a neural network based on slightly different version of GAN(Generative Adversarial Networks) was deployed, that get finely tuned during training, and it is discovered that when the network is well-trained to predict the masked patterns of natural resources sequences, then its internal weights are actually capturing, or "understanding", material structure. The Information about the structure being modelled develops within the network, and the resource structure is predicted from the patterns activated inside the network and the desired conditions and patterns were synergistically combined with automation in Space Robot and may lead to improved yield when graphically interpreted.
This paper presented an autonomous learning agent in a planetary environment for layering the presence of robots and tracking the environment that use encoded model, AI and learning mimicking the real world execution by space robots. and the results show that the real individual behaviour on a distant planet can be achieved provided the interplanet internet is available as pathway communication.

REFERENCE

1. **Poondru Prithvinath Reddy**: **"Metaverse in InterPlanet Internet: Modeling, Validation, and Experimental Implementation ", Google Scholar**