Unmanned Vehicle For UG Mine Inspection

Project no: **PSF-IH-1Y-009**

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Project Report

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Acknowledgment

We would like to primarily thank TexMin, IIT(ISM) Dhanbad for providing us an opportunity to work with such a diverse and applied project. This project involved various dimensions be it Machine Learning, Mining engineering, or Robotics and we are grateful to the organization for believing in us to successfully explore the areas and get the work done. We are highly grateful to our Guide and Principal Investigator Prof. Siddhartha Agarwal for his constant guidance and active involvement in the discussion of ideas. Additionally, we thank Prof. Dheeraj Kumar, Director of TexMin IIT(ISM) Dhanbad for his constant support, and Prof. Rajiv Sekhar sir, Director of IIT(ISM) Dhanbad, who has been of great support to the project and the whole idea of TexMin. We are grateful to have this opportunity to work on bigger projects on our campus and hope to make this project a great success.

Introduction (Problem Statement)

Mineral consumption is increasing rapidly as the population is increasing and as the global standard of living increases. The world is dependent on mineral resources to provide raw materials for manufacturing, construction, digital industry and to fulfill energy needs. As a result, underground mining continues to go to even deeper levels to tackle the requirement. However, deep underground mines are a very technical and challenging environment, requiring very robust and innovative technologies for economic gains and maintaining safety standards for people working in them. The underground environment is challenging due to high rock stress, high temperatures, poor communications with the surface, restricted access and lack of access to satellite positioning systems, presence of many harmful gases like CO, SO2, CH4, increased levels of CO2, etc, rock falls. The mining industry is committed to operating safely and reducing accident numbers, and it is increasingly migrating underground as surface deposits are exhausted. This report outlines a novel approach for providing mine rescue support and training through the combined use of unmanned ground vehicles (UGV) and unmanned aircraft systems (UAS) teams. The primary focus of this effort is the development of capabilities enabling effective mine rescue operations by reducing human exposure to harmful and dangerous environments. The secondary focus of this proposal is on integrating this capability into training scenarios as it is proven out and approved by DGMS. The application of this technology and resulting rescue/training methodology applies to underground gold and hard rock mining operations. Initial operations are targeted locally at the longwall operation in IIT (ISM) demo mine of the Mining Engineering department.

Why do we need automation in Indian mines?

Mining is a global industry that is fundamental to every product we use. A vital component of the mining industry is efficiency because most of the production revolves around transforming matter into different forms. It is often the case that

small improvements in execution speed, process efficiency, or reduced downtimes separate a profitable operation from a complete failure. Nowadays, artificial intelligence is readily available in many of the products and services we use. Furthermore, cloud computing matured, hardware prices decreased, and machine-to-machine communication improved, leading to unexpected advances in mining and industrial technology. Further, the increases in analytics and artificial intelligence to the mix and one gets the perfect environment for improving efficiency in all areas of a mining operation. Fatalities have always been one of the most concerning happenings in the mining field. Due to its large numbers, many times mining is not considered a safe profession to choose. The accidents are sometimes uncertain and unpredictable where the possibility of saving lives becomes difficult. Also, due to a lack of information on the actual incident site, it is often harder to save lives. However, Mining fatalities have been on a decreasing trend since the Mines Act which came into effect in 1952. However, during the last few years, a large number of miners lost their lives in work-related fatal accidents (DGMS, 2010-2019). The majority of the accidents and fatalities involved personnel and miners with less than 5 years of experience in particular jobs. Emerging technology gains in the area of unmanned aircraft systems (UAS) offers unprecedented capability in responding to emergencies, protecting valuable resources, and safely maximizing production time in mining operations. The integration of UAS and unmanned ground vehicles (UGV) into mining operations provides several key benefits. UAS/UGVs provide valuable support in emergency response situations, providing a critical first-look capability that can inform incident commanders on the best and safest employment of human assets.

Previous work

A lot of research has been done in this field about the application of mobile robots, sensory systems Including gas detectors, infrared thermography, image acquisition, advanced analytics in underground mining environments. Few viable applications of these robots are to create a 3D map of the environment, provide crucial sensor information which can be used to predict dangers and issue warnings in advance, and provide data regarding people working in the mine. In many cases, autonomous robots were built to provide immediate help to the people working in the mine and assess the situation. In most cases, a stereo

camera setup or lidar is used to create a 3D reconstruction of the environment and wheel encoders are used for getting odometry data.
There have been previous attempts by a team of researchers at Carnegie Mellon back in 2004 where they explored the area of 3D mapping the inside of a mine using multiple 2D Sick LiDARs. This research effort was led by Dr.Sebastian Thrun, one of the prominent researchers in the field of Robotics in the modern-day. A 2 Lidar system was employed, one for horizontal 2D Mapping and one for Vertical Mapping and using the information from the two 3D Volumetric Maps was built. In the modern-day, the availability of 3D Lidar Scanners has made it easier to explore the mines in a much more efficient way with a Single Sensor.
One of the first challenges by the Defence Advanced Projects Research Agency(DARPA) encourages various teams around the globe to explore the solutions for navigation of robots inside an Underground Mine environment. The ultimate aim of the competition is to achieve Autonomous Navigation in mine-like environments. Many Universities participating use a combined approach of aerial and ground vehicle robots, while some others carry out the Navigation task only with the help of Ground-based Robots. One of the significant methods listed was WildCat SLAM[2] by CSIRO Data 61 Robotics and Systems Group Australia. Another approach that researchers in the challenge have tried on is involving 3D Mapping using the Google Cartographer.

Objectives

The TIH in Mining 4.0 is aimed at achieving the following objectives in context to Exploration, Mining, and Mineral Processing:

1. Enhance Resource Discoveries and Locating deep concealed deposits
2. Get Real-Time Data
3. Reduce Risk: Integrated Technologies (CPS Systems) for Safe Mining
4. Smart & Sustainable Mining
5. Simplify Mining Operations

Our specific project aims for the following objectives:

- Mapping of UG Mines using Autonomous Robots
- Inspecting Hazards in Roofs of UG Mines, attain a higher level of safety and accuracy

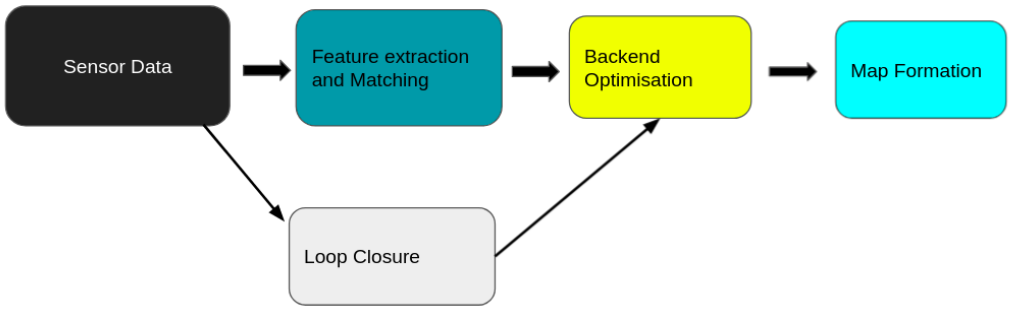
1) we can deploy a UGV attached with suitable sensors with the ability to autonomously take images
2) process those images to issue early warnings
3) help mitigate any risk of roof fall or overhangs and also assist us to gather a massive amount of data quickly
4) The UGV will not only find cracks and abnormalities but also provide their location on the map so that the risky areas can be found out and marked

- Object detection and Mine Personnel Tracking in an Underground mine through RGB cameras
    1. Analyze the images for detection of the number of mine workers and their postures.
    2. Face detection of the mineworkers inside the mine.

Why SLAM for underground ground vehicles

The most important question that comes to our mind when we think of an autonomous robot is how it will work in an unknown environment and will navigate through it. The most obvious solution could be GPS. But GPS has certain limitations and it cannot be used in underground conditions as it cannot cross through walls and it's not very accurate. So in these types of underground or enclosed situations, SLAM algorithms are used. So what slam does is provide the ability to a robot to create a map of its surroundings and localize itself within that map. Using a stereo camera setup or Lidar it can be used for 3D reconstruction of its surroundings. This will not only help in navigating through unknown places but will also help in avoiding collisions and can even be used for taking volumetric measurements in a mine.

SLAM Pipeline



Mapping in UG Mine using Autonomous Robots

UG mines are usually places with a lot of hazards involving, the release of harmful chemicals, rock falling, etc, and hence are usually harmful to a human. The use of Autonomous Robots in the Mines to inspect and map various areas of the mine is a safe and viable option. Autonomous Robots have various sensors built on them which help them understand the surroundings and create a spatial 3D map, which enables further analysis of the mines.

Robots enabled with LiDARs(Light Detection and Ranging), Depth Cameras, and Thermal Cameras can perform complex functionalities like localizing themselves and providing a high-resolution point cloud map of the surrounding by using the onboard processors and sending the map back to a remote operator at the base station. The method involved in forming the map is known as SLAM(Simultaneous Localisation and Mapping). More about this will be discussed in the Methodology section.

Roof hazards in UG Mine

The key risk in UG mines is geotechnical because ground stress conditions are very high at depth and stress distribution takes place after every blasting process. Now, this requires an essential geotechnical inspection of the freshly blasted face for which the mining sirdar goes to that place manually to inspect the roof conditions. This process is very dangerous, time-consuming, and subject to human error. Geological failures such as roof collapse and rockfalls are some of the most fatal and common safety hazards in an underground environment. The presence of surface cracks is one of the early signs that could lead to geological failure. Roof hazard conditions are generally assessed by visual inspections and knowledge gained through observational techniques which involves sending a person to an area that the surroundings are very risky and unsafe. Roof fall hazard assessment techniques proposed in different literature and practiced by the industry, largely depend on visual observations and expert opinion. Image data has a promising potential in developing an autonomous hazard detection system since the current roof fall hazard assessment techniques depend on visual clues. The development of a convolutional neural network system that classifies roof fall hazard levels based on roof images is

explained in this paper. The crack detection method consisted of mainly two parts, first is image processing which involves the use of various filters for the detection of crack, and the second was CNN which involved collecting a data-set of images, which is then fed into the model for training and making further predictions.

Object Detection, Personnel tracking, and Face Detection

The performance of the exploration system is evaluated in terms of its ability to detect and locate potential victims as well as objects that provide a cue of their location. Object detection is performed by every robot of our team by processing camera data by a neural network using a customized version of the YOLOv4 object detector. If the robot has a 3D map of its surroundings, the bounding box provided by the YOLOv4 detector is projected into the 3D map. Then, the final position of the detected object is established over the temporally consistent detections. Only if the detection is certain, the robot send position and RGB snapshot of the detected object. This prevents flooding of the communication network with image data, potentially preventing other robots from reporting the objects detected. Since the rules explicitly prohibit training the neural network at the mine where the challenge occurs, we trained the YOLO on imagery gathered in other mines. Good performance of the detection method during the contest indicated a good ability of the neural network to generalize the training data.

Methodology

SLAM for UG Mines

Autonomous Robots are those which are capable of exploring the environments around them and safely reaching the desired location along with keeping track of their location at all times. One of the main abilities for such a robot is the capability of performing SLAM.

The next obvious question is what exactly is SLAM. SLAM stands for Simultaneous Localisation and Mapping. As the name suggests the Robots localized and map their environment all at the same time. Localization fundamentally answers the question "Where am I ?" and Mapping is the phenomenon of capturing the surrounding environment and creating a map.
SLAM based on sensors is of three types:

- Visual SLAM
- LiDAR SLAM
- Visual-LiDAR SLAM

A Visual SLAM depends only on the data captured by cameras, usually a depth/stereo camera system. This kind of system is not entirely reliable since images might be adversely affected by many factors like lighting conditions, motion blur, occlusion, etc.

A LiDAR-based system deals with using a point cloud to deal with the process of Mapping and is more reliable but also a costlier approach when it comes to 3D LiDAR Mapping.
Underground Mines is one challenging area for an Autonomous Robot to perform SLAM. One of the major principles of SLAM is that it works by registering or identifying certain unique types of Landmarks. Owing to this fact when a robot performs Autonomous Navigation in long uniform corridors the SLAM system is bound to be confused and thus leads to losing track of where the robot is present. A similar case might occur in the case of Mines but the rocky interiors could provide some unique identification w.r.t to the surroundings and there might not be such a scenario in a mine. An Additional pressing issue would be that a Mine Scenario is a rather ill lightened situation and use of a purely visual system would lead to very poor images and hence using a LiDAR and a vision system combined would be a better approach.

After reviewing many open-source approaches, we decided to implement the RtabMap SLAM method initially in a simulated Cave environment on the Gazebo Software simulator. The Robot used was a simple 2 wheel drive Turtlebot enabled with an Intel Realsense Depth Camera. The Robot can move through the environment and perform the mapping process. The images below show the application of RtabMap for an indoor house-likeFiguresAppearance-based optimization visualize environment.

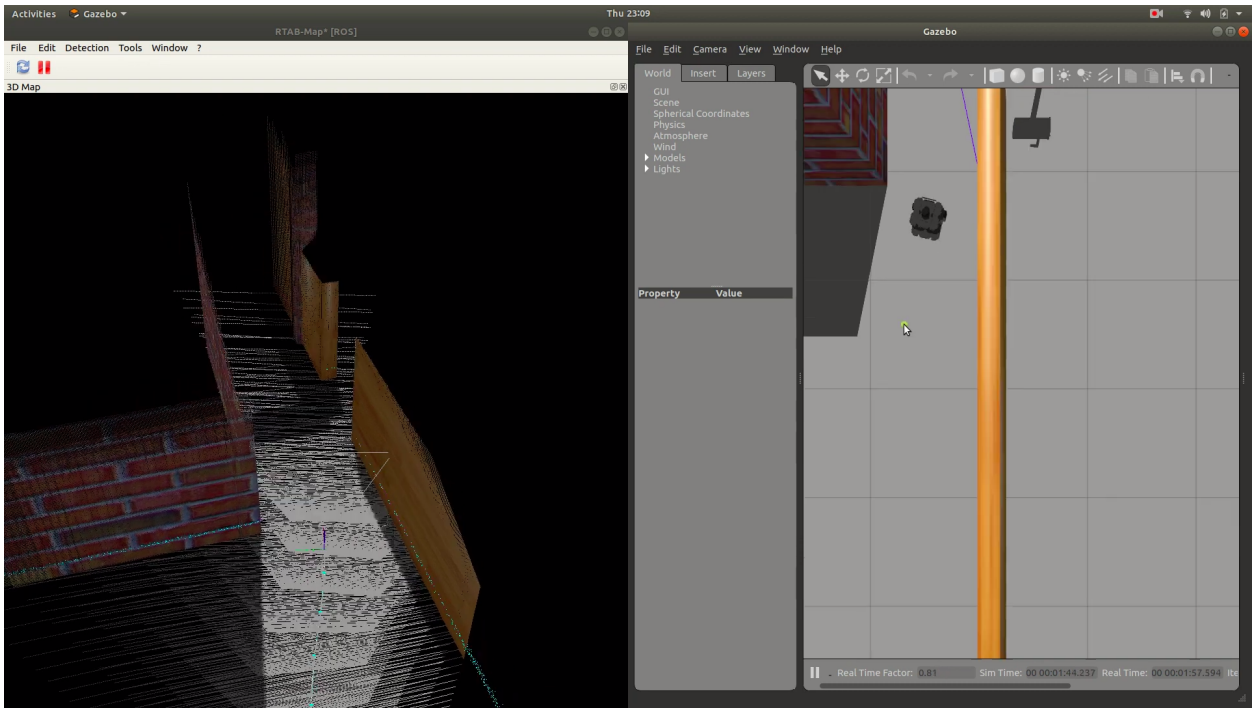


Fig.1

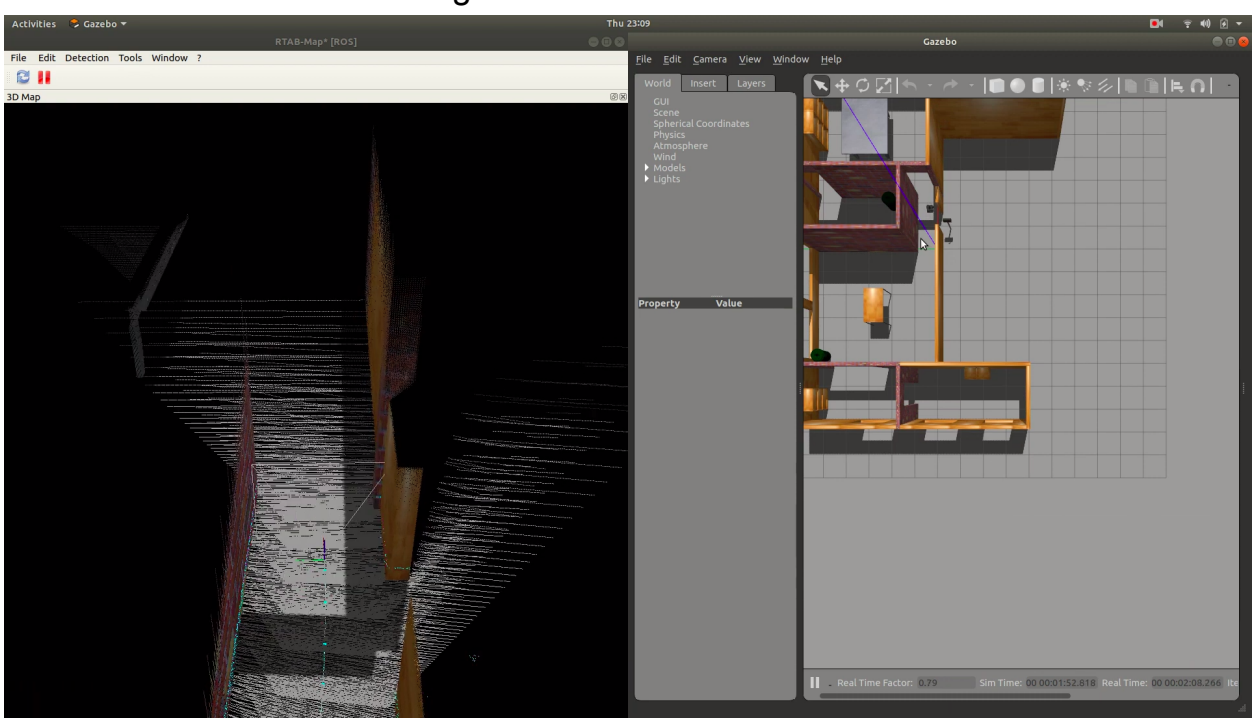


Fig. 2

Figures 1 and 2 show the indoor environment of a house being mapped using the RTabMap SLAM.

RTABMap(Real-Time Appearance-based Mapping)

RtabMap is a Visual SLAM method performed using a depth camera/stereo-camera pair. **RTAB-Map[3]** (Real-Time Appearance-Based Mapping) is a RGB-D, Stereo and Lidar Graph-Based SLAM approach based on an incremental appearance-based loop closure detector.RtabMap leverages the advantage of being a Graph Slam method by using repeated loop closures to align the scenes perfectly. This method is preferred over the others since it performs real-time backend pose graph optimization and feeds the map to the frontend for further tasks like Loop closure detection.

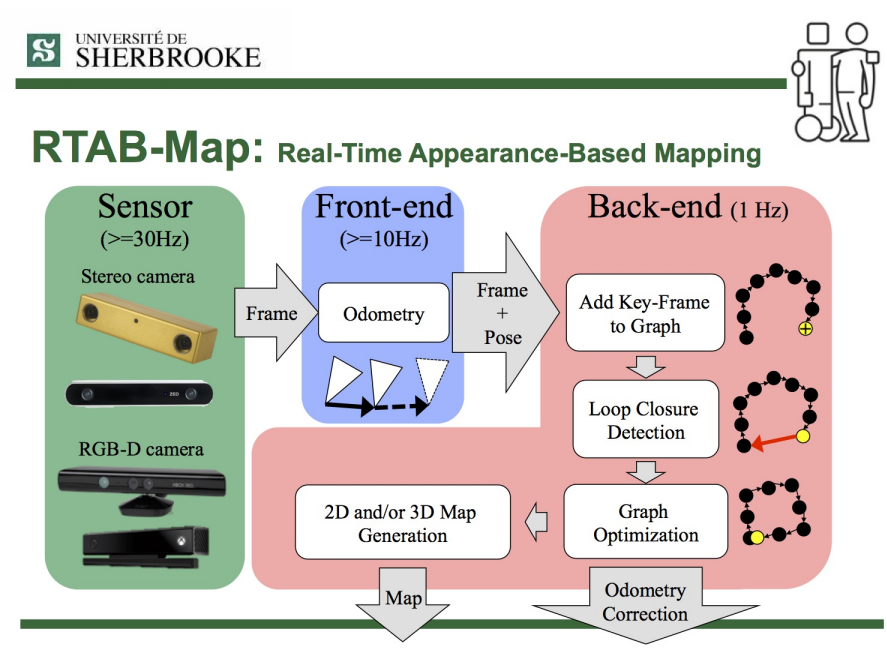


Fig.3 RTABMap SLAM pipeline

Crack detection on roof and wall surface

First using a camera, high-resolution images of the target are collected. The images are pre-processed using image processing techniques to reduce noise, remove shadows and adjust other properties such as size and brightness of images. The images can also be converted to grayscale to decrease the

computational time. The resultant image is applied to the crack detection procedure which uses image processing techniques like edge detection, pixel analysis to predict whether the crack is present or not. The crack detection starts with an image analysis step where a canny detector and thresholding technique are used to visualize the cracks more clearly. A canny edge detector is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It uses a multi-stage algorithm to detect a wide range of edges in images. The second technique used is thresholding. Thresholding is a method in which pixel values below or above a predefined threshold are replaced by white or black values depending upon the requirement. A threshold of 155 was used to visualize the cracks in a clear way. To get a more clear visualisation of cracks we can also use a combination of canny applied after thresholding.

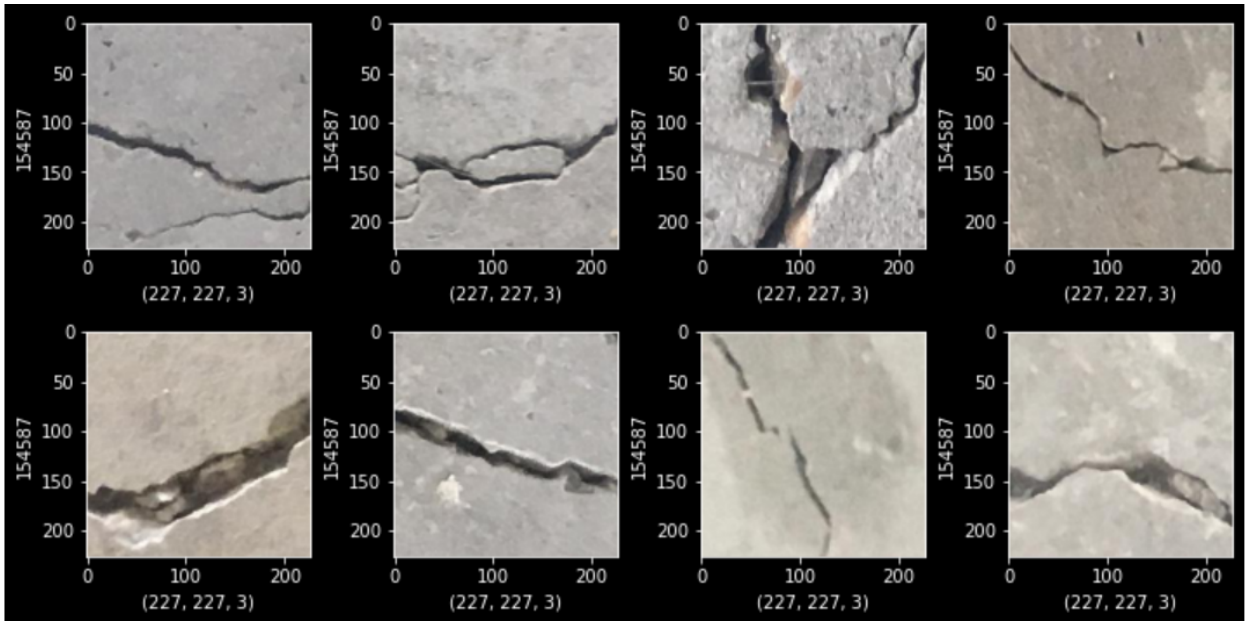


Fig-4 (Training images)

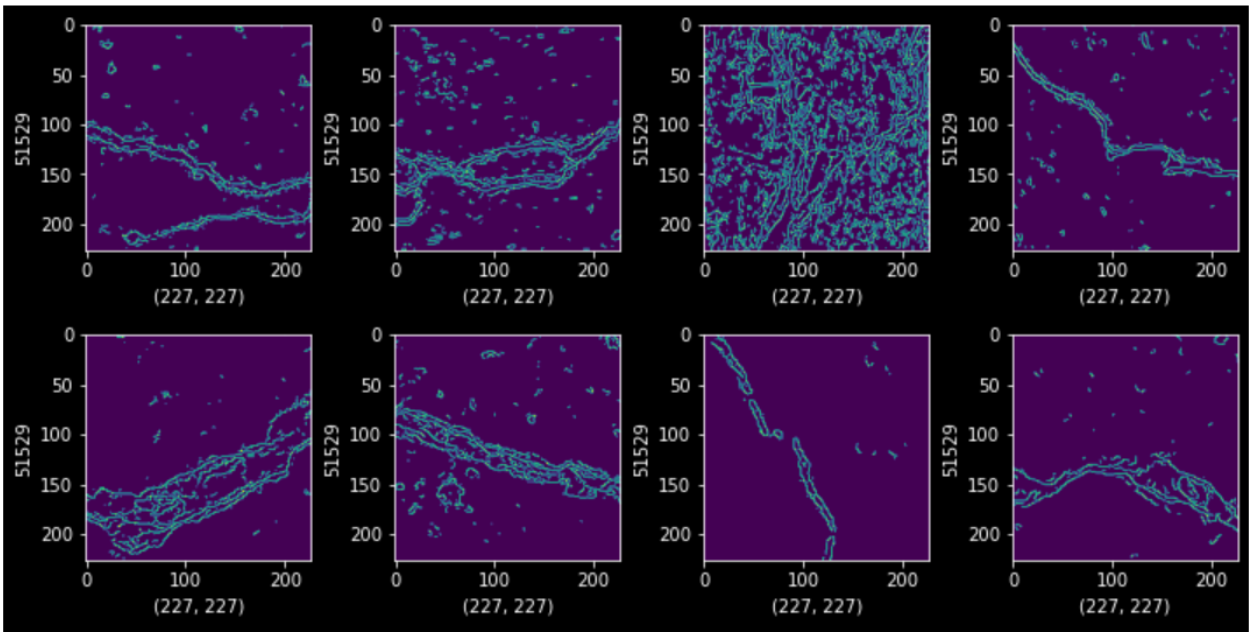


Fig - 5(Images after applying Canny Detector)

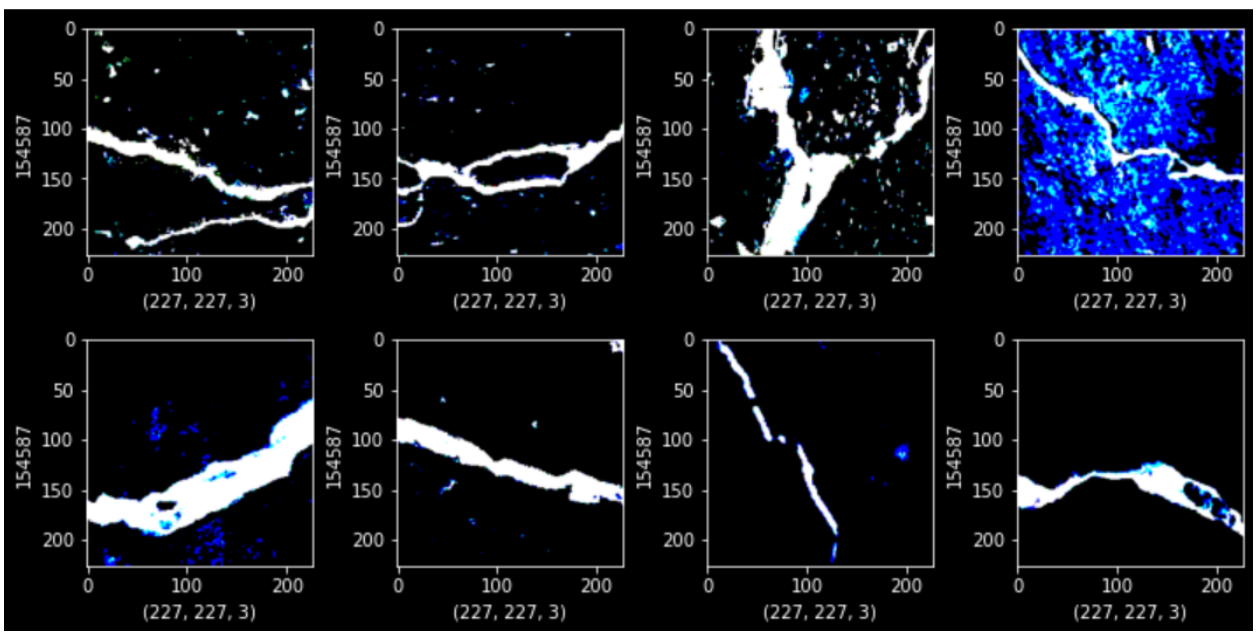


Fig-6(Images after applying Threshold)

After the image analysis part, a CNN model was applied to detect cracks. The CNN model has three layers of neurons: convolutional layer, pooling layer, and fully connected layer. The convolutional layer extracts features from images which enables it to distinguish between crack and non-crack images. The role of the Convolutional layer is to reduce the images into a form that is easier to process, without losing features, and which are important for getting a good prediction. After each convolution operation, a CNN applies a Rectified Linear Unit (RELU) transformation to the feature map, to introduce nonlinearity to the

model. The pooling layer is used for down-sampling the image and reducing its size by adjusting its dimensions. The pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is used to decrease the computational power required to process the data through dimensionality reduction. There are two types of Pooling: Max Pooling and Average Pooling. Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel. Max Pooling also performs as a Noise Suppressant. It discards the noisy activations altogether and also performs de-noising along with dimensionality reduction. After going through the above process, we have successfully enabled the model to understand the features. After applying multiple convolutions and pooling layers, we are going to flatten the final output and feed it to a regular Neural Network for classification purposes. A fully connected layer is used in the final stage of a CNN model, as it takes the output from the previous layer as input and maps it to an output label In the machine learning model.

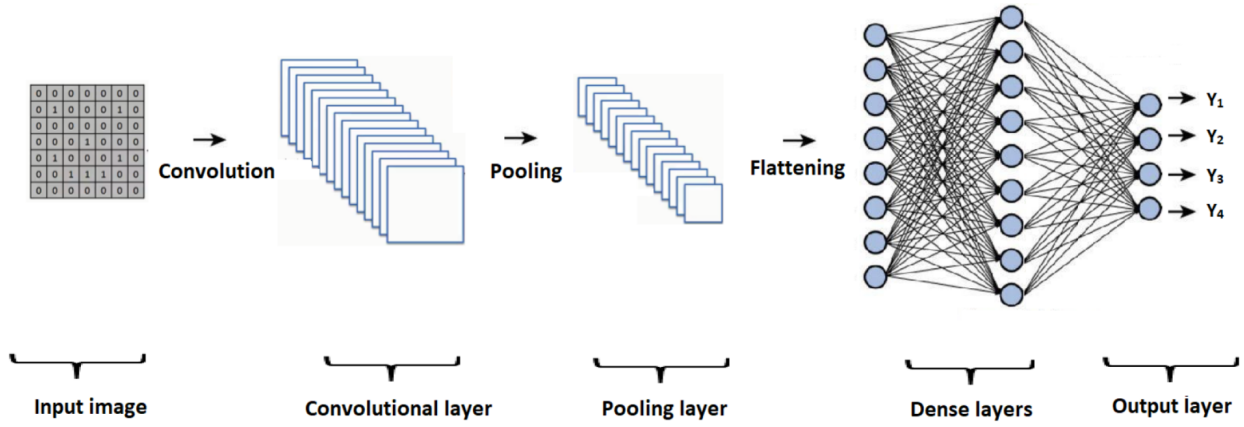


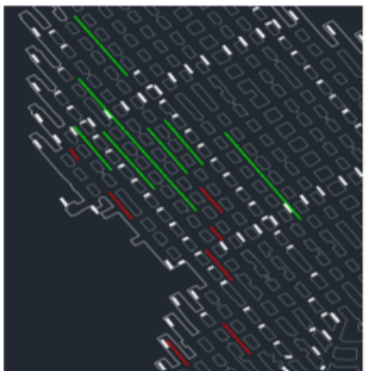
Fig-7

In our case,, 40k images consisting of 20k images with cracks and the remaining 20k without cracks were taken for training. To reduce computation time images resolution was reduced to 227*227 with RGB channels. The images were normalized to give consistent results. Then a combination of convolutional layers and max-pooling layers were applied to get the feature vector. Then the feature vector is flattened and fed into a densely connected neural network and appropriate parameters were selected to make predictions. The validation dataset was used to tune the hyper-parameters of the model. The model was then tested on cracked images of coal blocks shown in Fig-8 and the model was able to identify the cracks successfully.

Fig - 8

The next step in the process included collecting data from real mines and testing our model on that. For that we took images of cracks present in a longwall mine in the campus and tested our model on that where the model was able to identify most of the images with cracks. The next part in this detection includes increasing the accuracy of detection and making it scalable to be used in a real mine scenario.

The images above show the images taken from the longwall mine which was correctly identified.



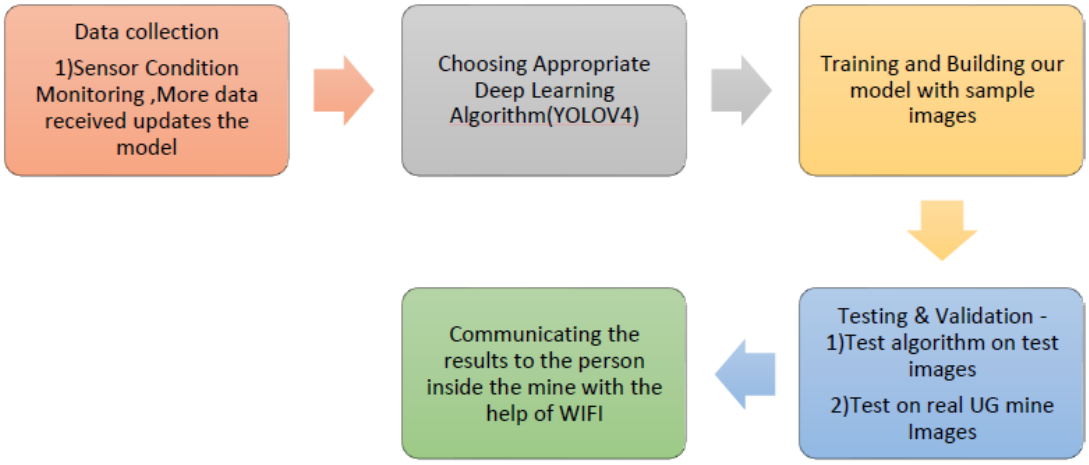
A map of the mine as shown beside can be developed which shows different parts of the mines where cracks are present and can be hazardous so that adequate mitigation steps could be taken in advance. We can also keep a record of hazardous zones and people can be restricted from going there.

Fig. 9

YoloV4 for Object, People, Face Detections

Object detection

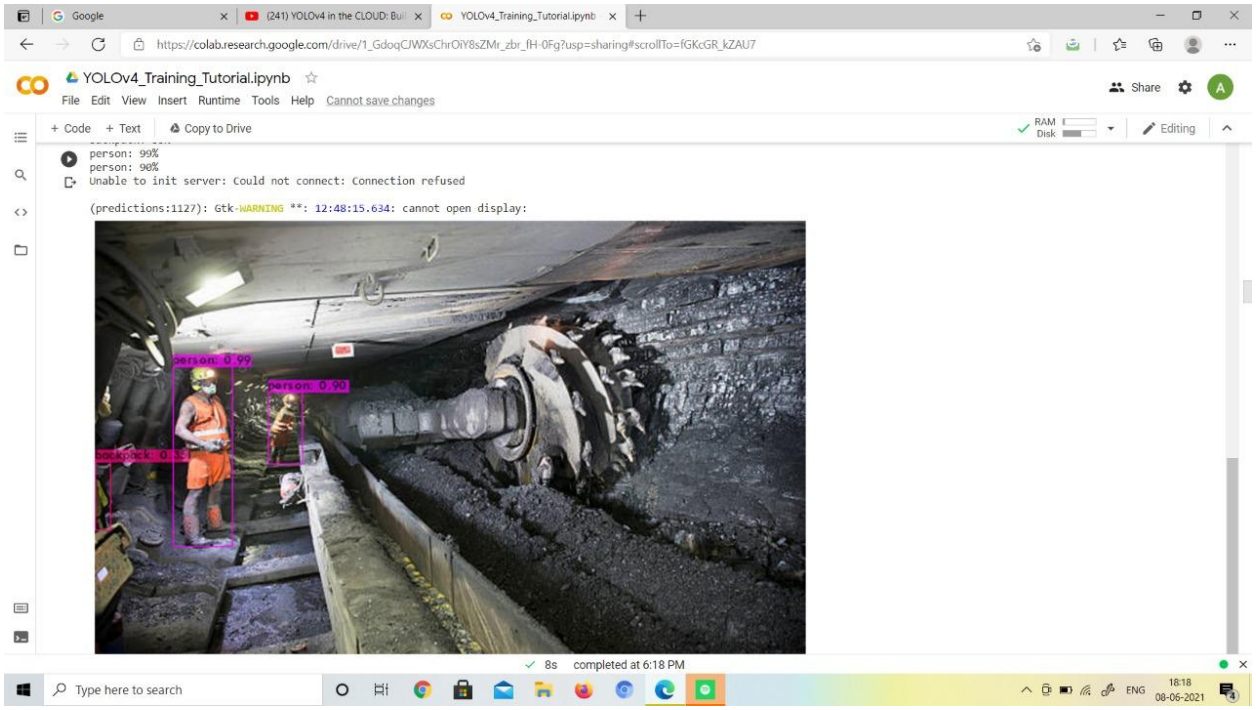
The performance of the exploration system is evaluated in terms of its ability to detect and locate potential victims as well as objects that provide a cue of their location. Object detection is performed by every robot of our team by processing camera data by a neural network using a customized version of the YOLOv3 [25, 26] object detector. If the robot has a 3D map of its surroundings, the bounding box provided by the YOLOv3 detector is projected into the 3D map. Then, the _nal position of the detected object is established by the application of Kalman _Fitering over the temporally consistent detections. Only if the detection is certain, the robot send position and RGB snapshot of the detected object. This prevents ooding of the communication network with image data, potentially preventing other robots from reporting the objects detected. Since the rules explicitly prohibit training the neural network at the mine where the challenge occurs, we trained the YOLO on imagery gathered in other mines. Good performance of the detection method during the contest indicated a good ability of the neural network to generalize the training data.



1. **OBJECT(PERSON) DETECTION IN UNDERGROUND MINE**

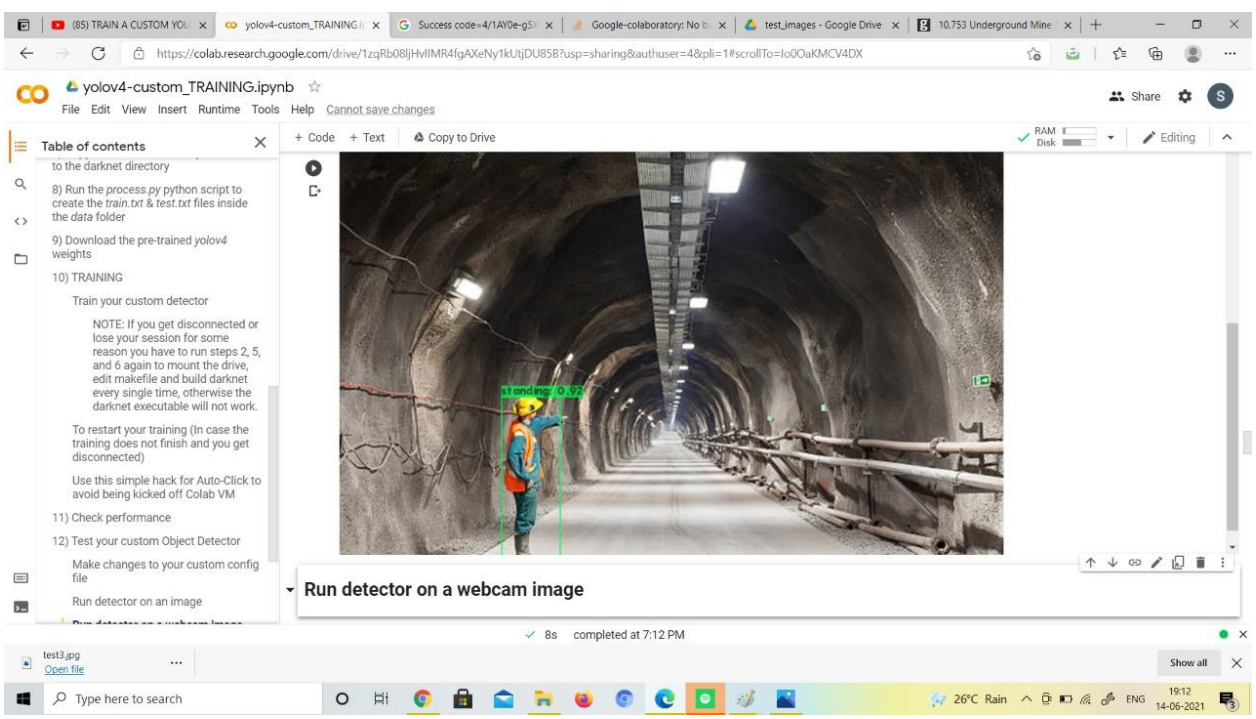
The performance of the exploration system is evaluated in terms of its ability to detect and locate potential victims as well as objects that provide a cue of their location. Object detection is performed by every robot of our team by processing camera data by a neural network using a customized version of the YOLOv4 object detector. If the robot has a 3D map of its surroundings, the bounding box provided by the YOLOv4 detector is projected into the 3D map. Then, the final position of the detected object is established over the temporally consistent detections. Only if the detection is certain, the robot send, position, and RGB snapshot of the detected object. This prevents flooding of the communication network with image data, potentially preventing other robots from reporting the objects detected.

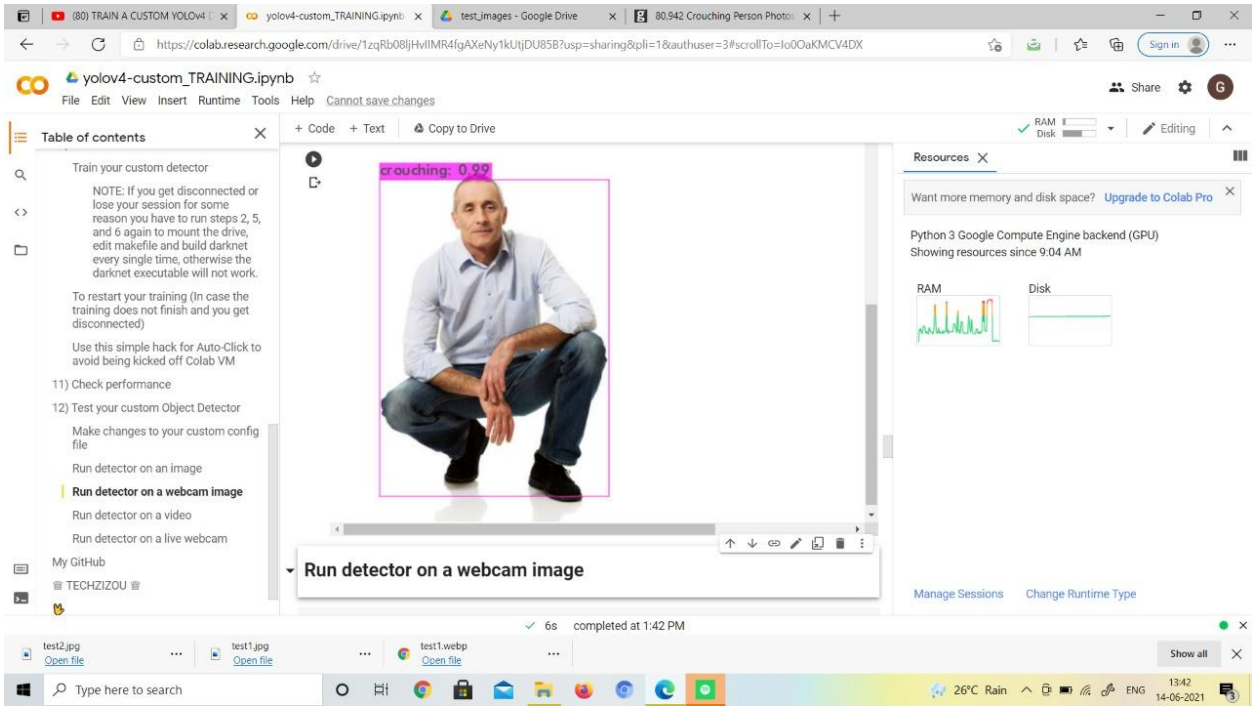
Since the rules explicitly prohibit training the neural network at the mine where the challenge occurs, we trained the YOLO on imagery gathered in other mines. Good performance of the detection method during the contest indicated a good ability of the neural network to generalize the training data. In this task, we used the predefined weights of the coco dataset in the darknet directory in yolov4. We first install the darknet directory by running the codes on Jupyter Notebook and then we install the coco dataset which uses the predefined weights and predicts the objects on the images.



2. POSTURE ANALYSIS

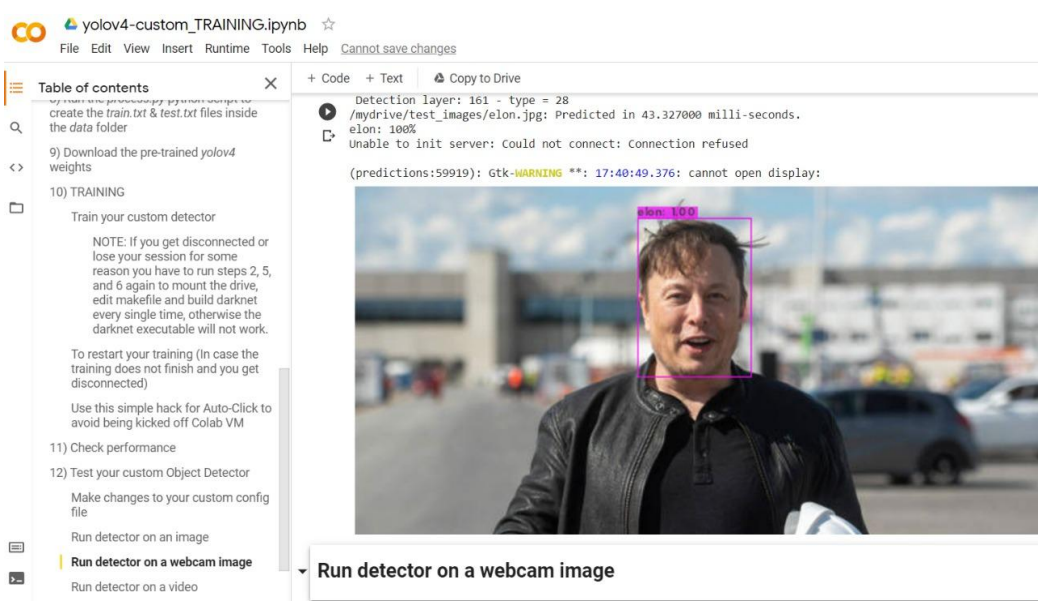
In this step, we do the same steps as we did in the previous one . Adding onto that we train our model on some training images of 3 different postures and then use the trained model to predict the same on some test images.

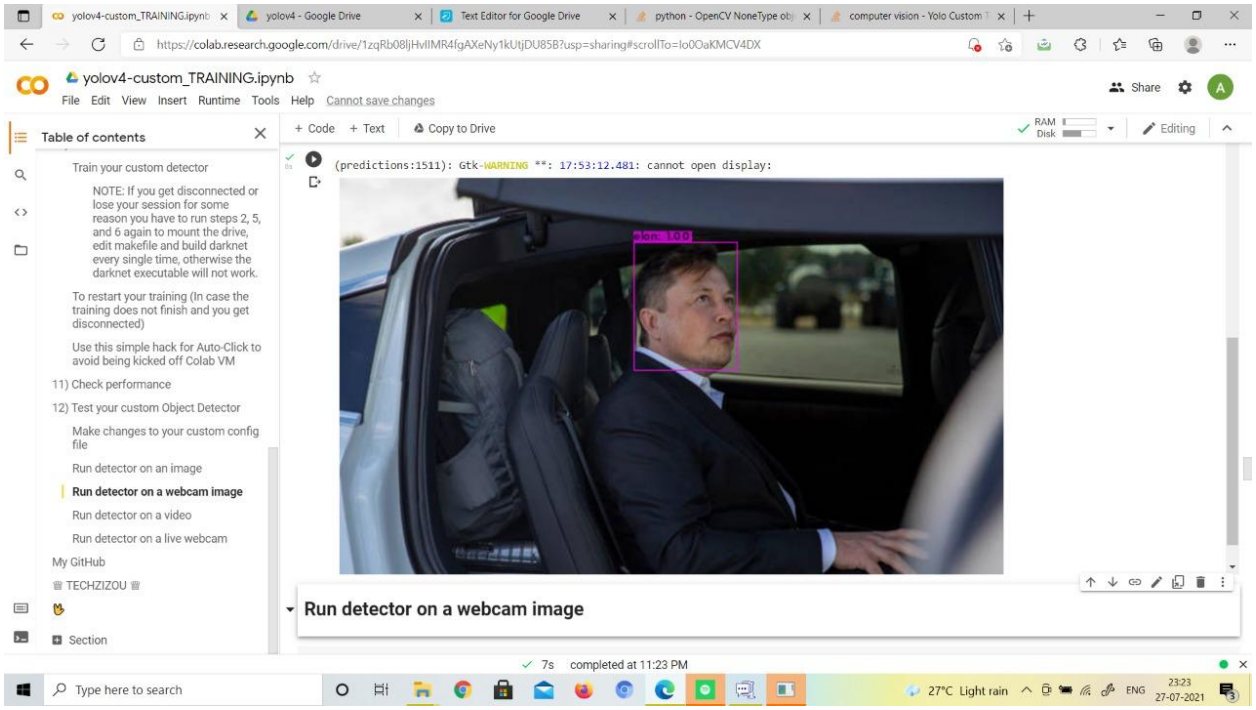


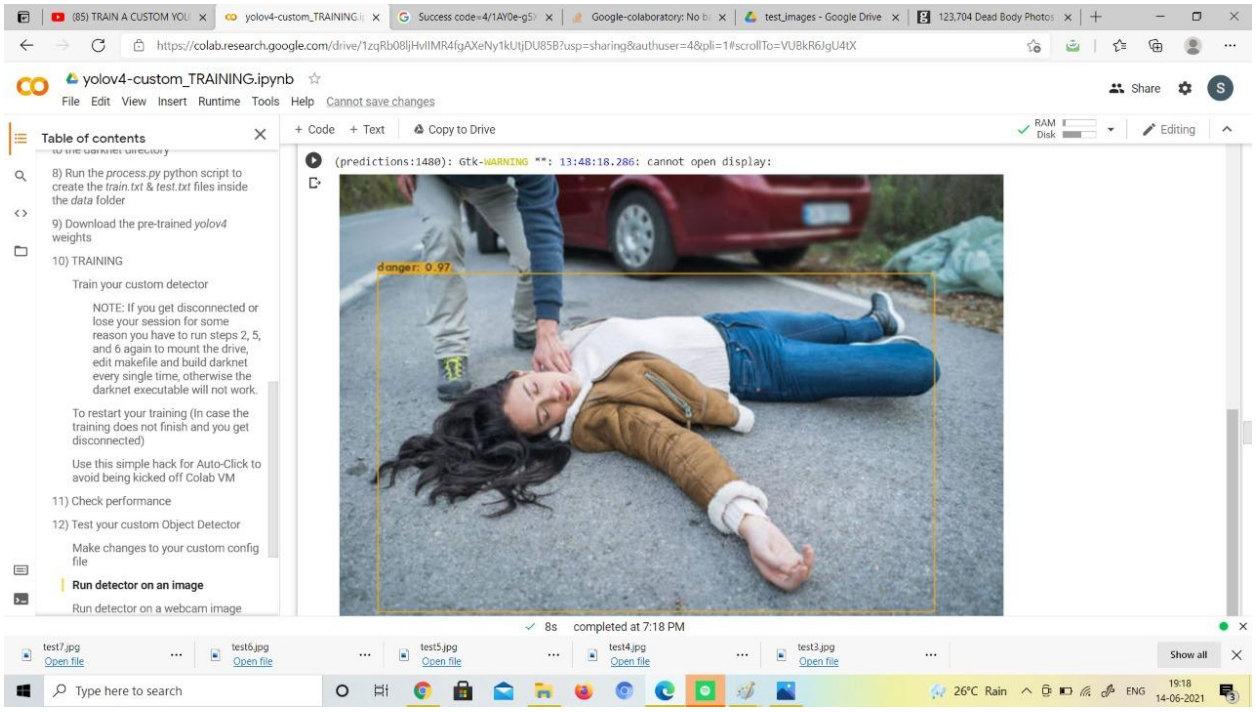


3. Face detection

In this step, we do the same steps as we did in the first one. Adding onto that we train our model on some training images of different persons and then use the trained model to predict the same on some test images.




yolov4-custom_TRAINING.ipynb
File Edit View Insert Runtime Tools Help Cannot save changes
Table of contents
Train your custom detector
NOTE: If you get disconnected or lose your session for some reason you have to run steps 2, 5, and 6 again to mount the drive, edit makefile and build darknet every single time, otherwise the darknet executable will not work.
To restart your training (In case the training does not finish and you get disconnected)
Use this simple hack for Auto-Click to avoid being kicked off Colab VM
11) Check performance
12) Test your custom Object Detector
Make changes to your custom config file
Run detector on an image
Run detector on a webcam image
Run detector on a video
Run detector on a live webcam
My GitHub
TECHZIZOU
Section
(predictions:1511): Gtk-WARNING **: 17:53:12.481: cannot open display:
Run detector on a webcam image
7s completed at 11:23 PM


yolov4-custom_TRAINING.ipynb
File Edit View Insert Runtime Tools Help Cannot save changes
Table of contents
8) Run the process.py python script to create the train.txt & test.txt files inside the data folder
9) Download the pre-trained yolov4 weights
10) TRAINING
Train your custom detector
NOTE: If you get disconnected or lose your session for some reason you have to run steps 2, 5, and 6 again to mount the drive, edit makefile and build darknet every single time, otherwise the darknet executable will not work.
To restart your training (In case the training does not finish and you get disconnected)
Use this simple hack for Auto-Click to avoid being kicked off Colab VM
11) Check performance
12) Test your custom Object Detector
Make changes to your custom config file
Run detector on an image
Run detector on a webcam image
(predictions:1480): Gtk-WARNING **: 13:48:18.286: cannot open display:
danger: 0.97
8s completed at 7:18 PM

Results from the LongWall Mine

This section is dedicated to the experimental results obtained at the Longwall Mine laboratory at the Indian Institute of Technology(Indian School of Mines) Dhanbad. A Longwall mine replica is present in the IIT(ISM) Dhanbad campus with equipment like the shearer.

The three major problems which we tried to solve in this physical mine like environment are:

1) Personnel Detection.
2) Crack Detection(already presented in a previous section).
3) SLAM Implementation in the Mine.

One additional task we had performed is the capture of “thermal imagery” which could further help with SLAM implementation and also detection of areas of with high amount of coal. We also show that, it is possible to transmit this thermal images to the base station via cloud in real time and process them further to obtain useful insights.

Personnel Detection:

To verify the YoloV4 model that we had trained for the custom task of personnel detection in the mine, we had asked some volunteers to stand in the Longwall mine depicting various mining activities like inspection of the roof, performing mining on the walls etc.

In this experiment, we had focused on things like detection of personnel and recognition of the people. Additionally, we had also focused on estimation of the posture of the person, with the aim that if a person is stuck somewhere in a mine in a certain position, the robot could orient itself in a proper way to save the person quickly.

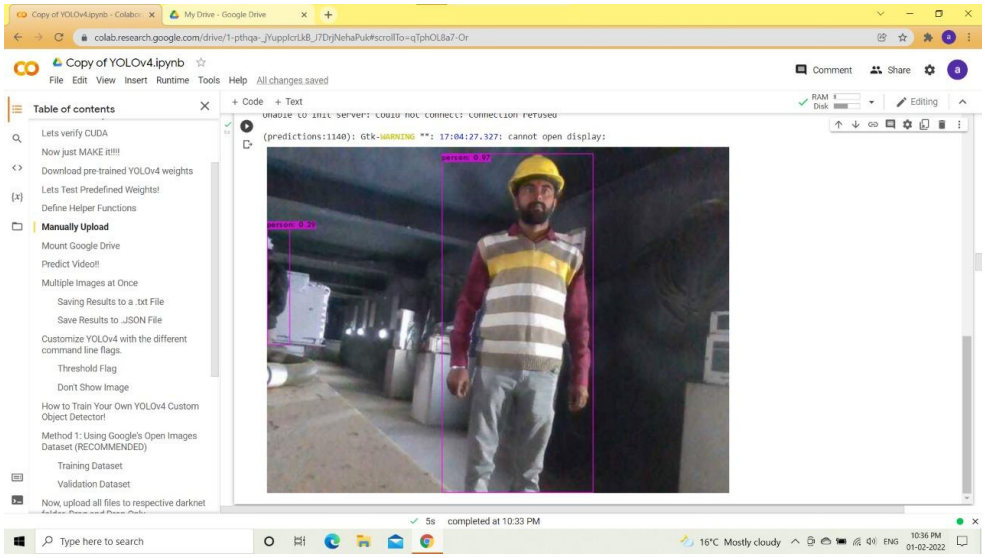


Fig. Picture depicting personnel detection.

This picture shows that our algorithm successfully detects people in the scene and is also shows exemplar performance in the case where there is only a partial person in the scene.

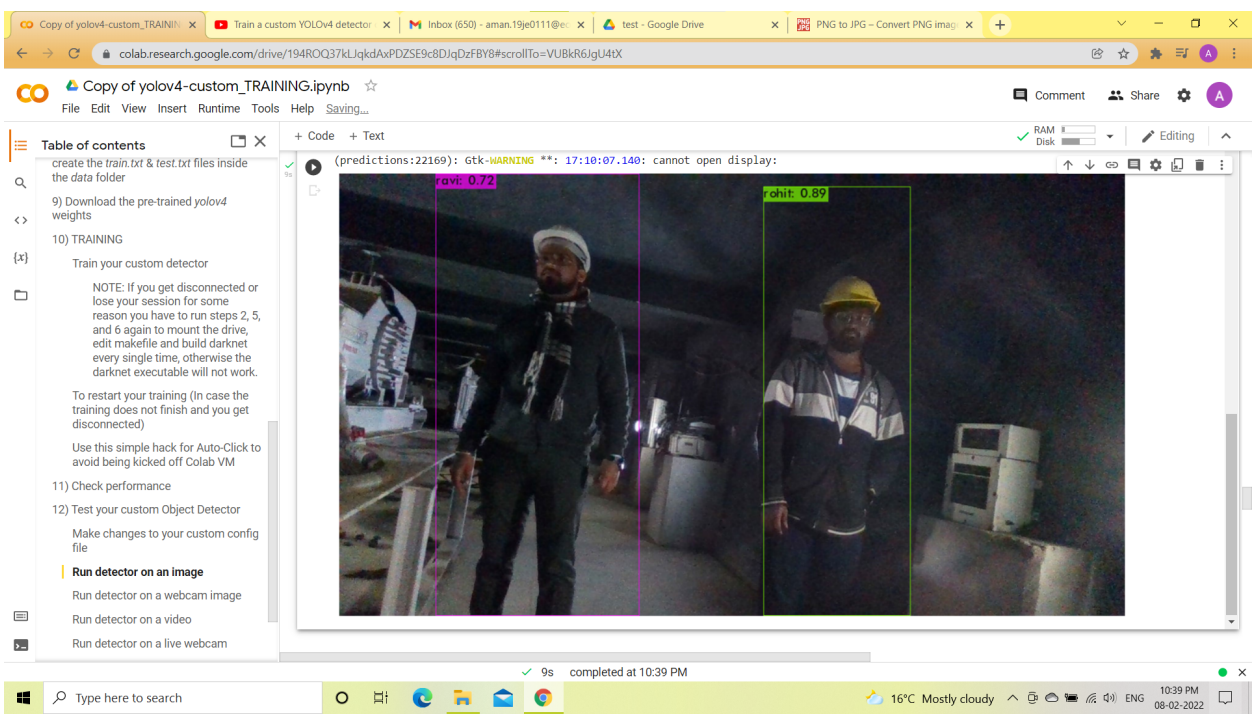


Fig. Person Recognition.

The above image shows the model correctly predicts the names of the people working in the mines. This will help us keep the track of the specific people in the mine.

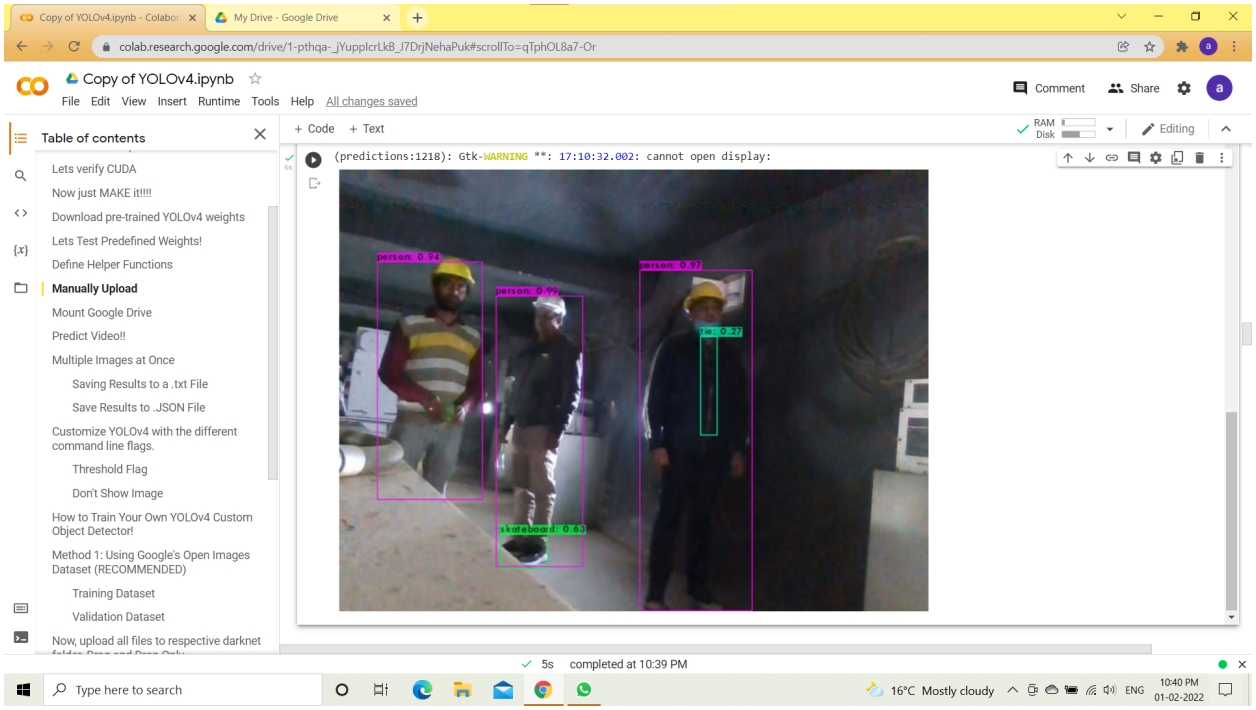


Fig . Picture showing detection of people and objects.

This image shows the model performance in the task of object detection along with personnel detection.

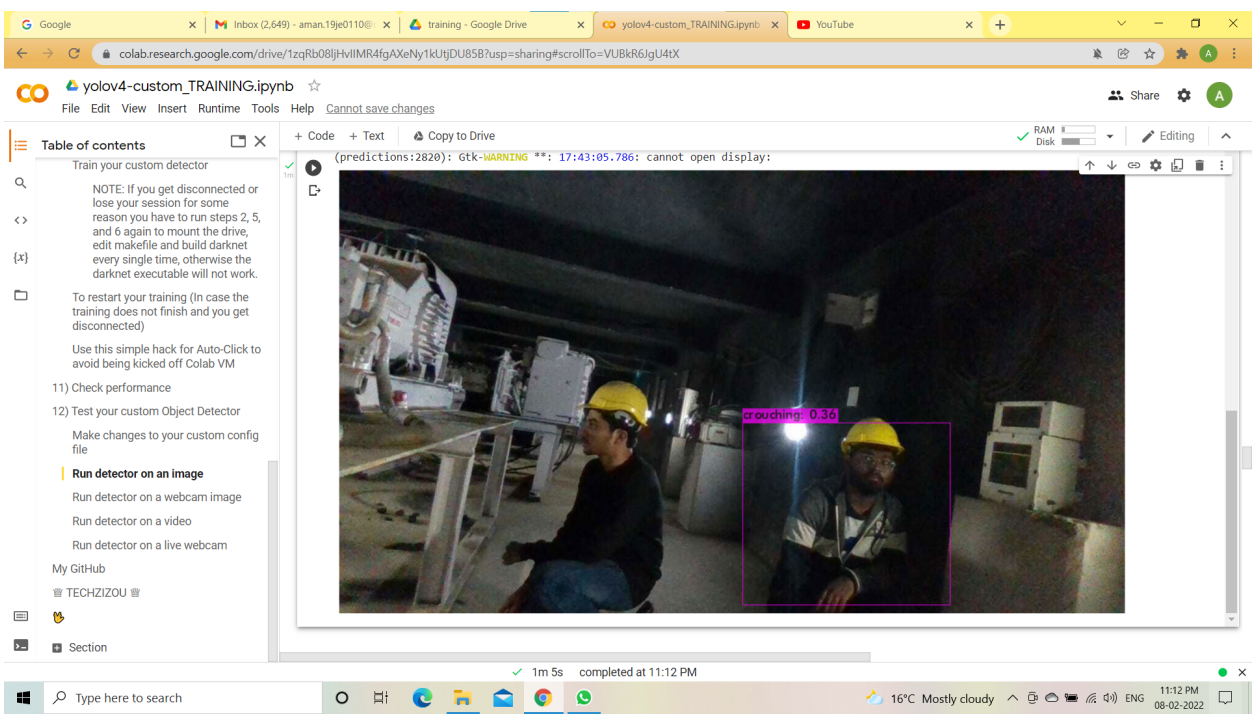


Fig. Image showing detection of Miner Posture.

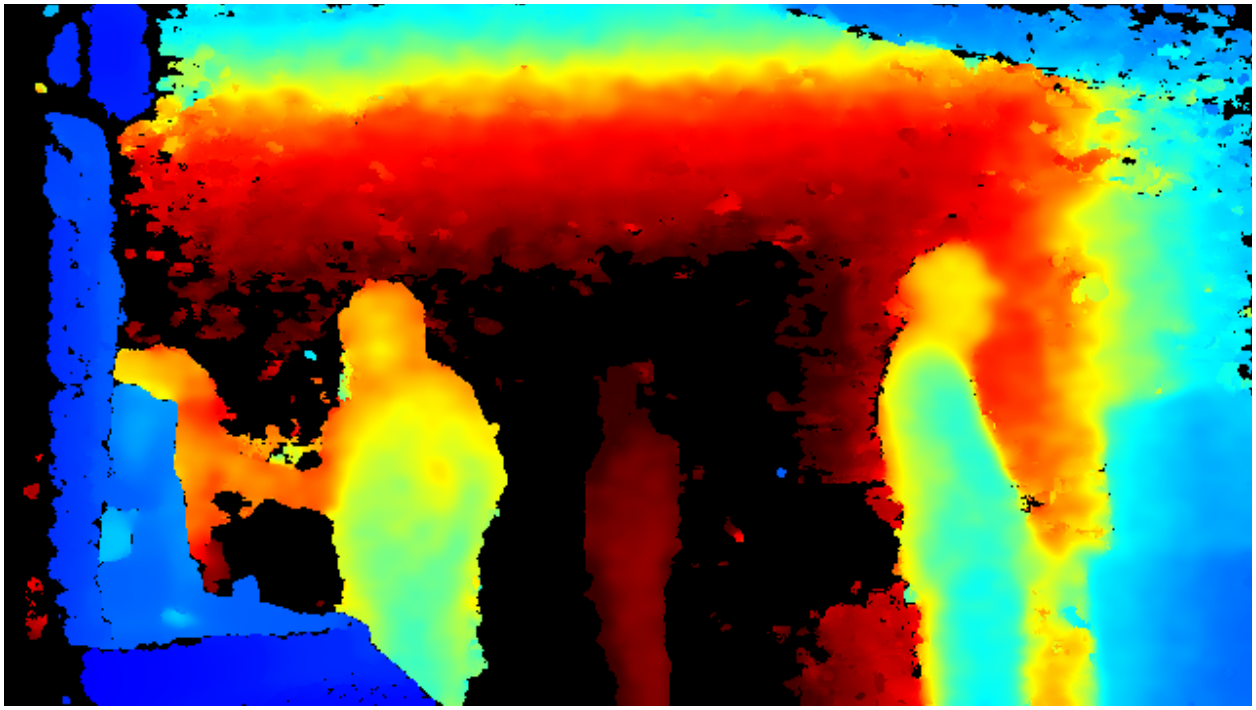


Fig. Depth Image captured by the depth camera.

The Depth Images help implement some Vision algorithms through which we can predict the distance of the personnel from the robot at close range and help in a more optimised approach in rescue operations.

SLAM Implementation:

RTABMap SLAM is used in the Longwall Mine to implement Visual SLAM as verified in simulation before.

An IntelRealsense D415i Depth camera was used to implement the RGB-D Handheld mapping scheme. In this procedure to form the map, the camera(in the future the robot) should know the location of itself with respect to the landmarks in the 3D scene. Using mathematical and classical computer vision techniques, the RTABmap SLAM method brings out the accurate position of the current state of the robot. Furthermore, to form a continuous map, the robot should know the amount of distance it has moved from its previous state so as to properly co-relate the image positions.This measure of robot displacement is called “Odometry”. In this case, due to the uneven surfaces in the mines, we rely on something called Visual Odometry, which calculates the distance between positions using visual methods.

Successfully, performing the odometry and localisation, the robot is able to form the map of the mine and thus will be able to autonomously navigate the environment.

Fig. 3D point cloud of the interior of the LongWall Mine Laboratory.

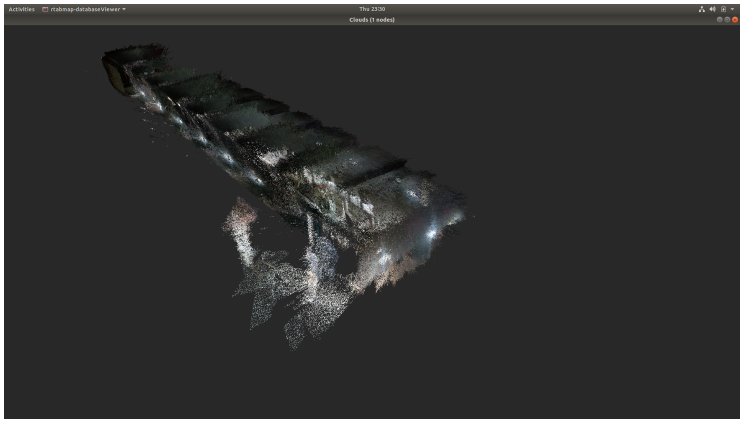


Fig. Top View of the map formed using RTABMap SLAM.

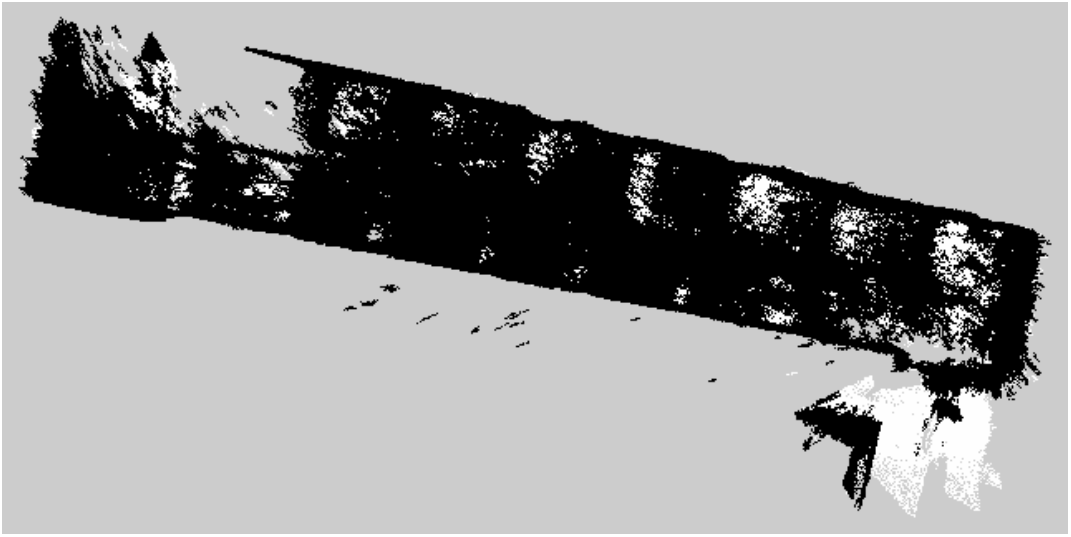


Fig. 2D occupancy grid.

This 2D occupancy grid combined with the 3D point cloud will help the robot detect and avoid occupied spaces shown in black in the image and navigate in the white spaces.

Thermal Imagery:

Thermal Images were taken using the FLIR Thermal camera. The experiment was to see how effectively the camera is able to capture the images and this could further help in utilization of thermal imaging for “Thermal Odometry”. Here some heated coal and some unheated coal is placed on the conveyor belt and is detected by the camera. The coal was very moderately heated yet the camera detects it with great distinction from surroundings.

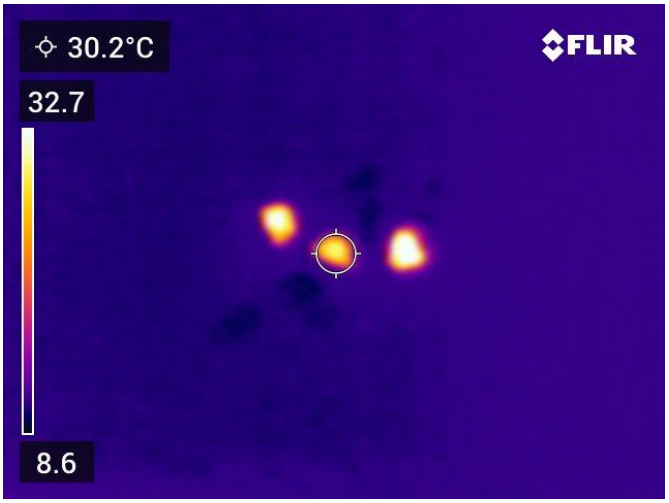


Fig. Thermal Image showing both heated and non heated coal.

Future Work

Sensor Integration

Upon the arrival of the actual robot and its parts, major tasks include integration of the sensors like Depth camera, thermal camera, and LiDAR sensor with the main onboard computer of the Robot. Furthermore, the inbuilt robot sensors which are essential for the autonomous operation of the Robot, like the odometers and IMUs should be properly tuned. The next step would further include capturing data from mine and performing crack detection on real mine images and finally making changes in the model to get good accuracy.

Communication Systems

One of the most significant issues to be addressed is that of communication between the robot and a base station. For a prototype level, if the control and the robot are in the same room, a local wifi network would be sufficient to connect the two. But in an outdoor environment, the Robot and the base station should have separate modems to connect to the internet and using Cloud Services data can be transferred.

In a real mine-like situation, the Robot is incapable of receiving signals deep in the mines, thus the Robot on its way drops Wifi receivers and these form a wifi node mesh network. At the base station, a High Gain antenna is used to transmit the Wifi Signal to the Robot

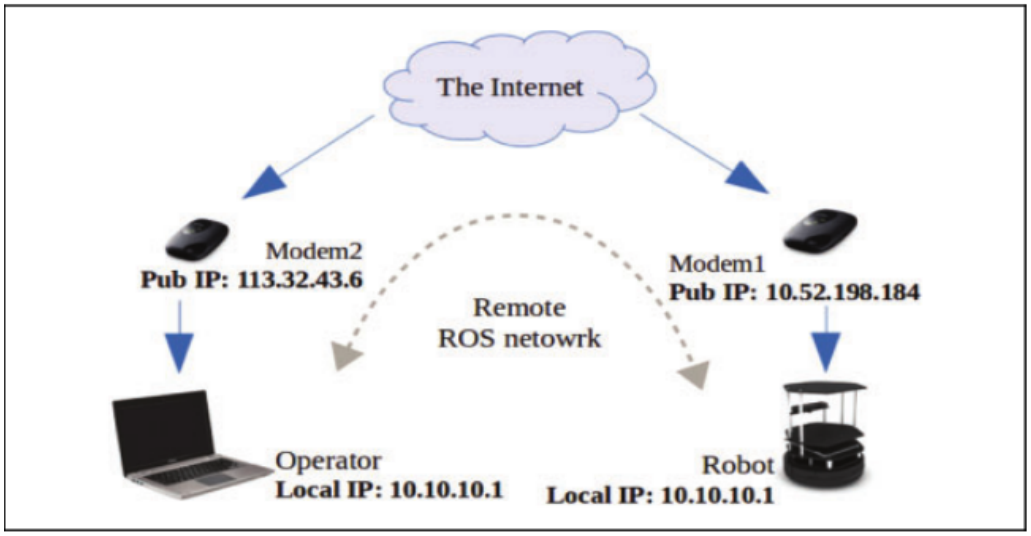
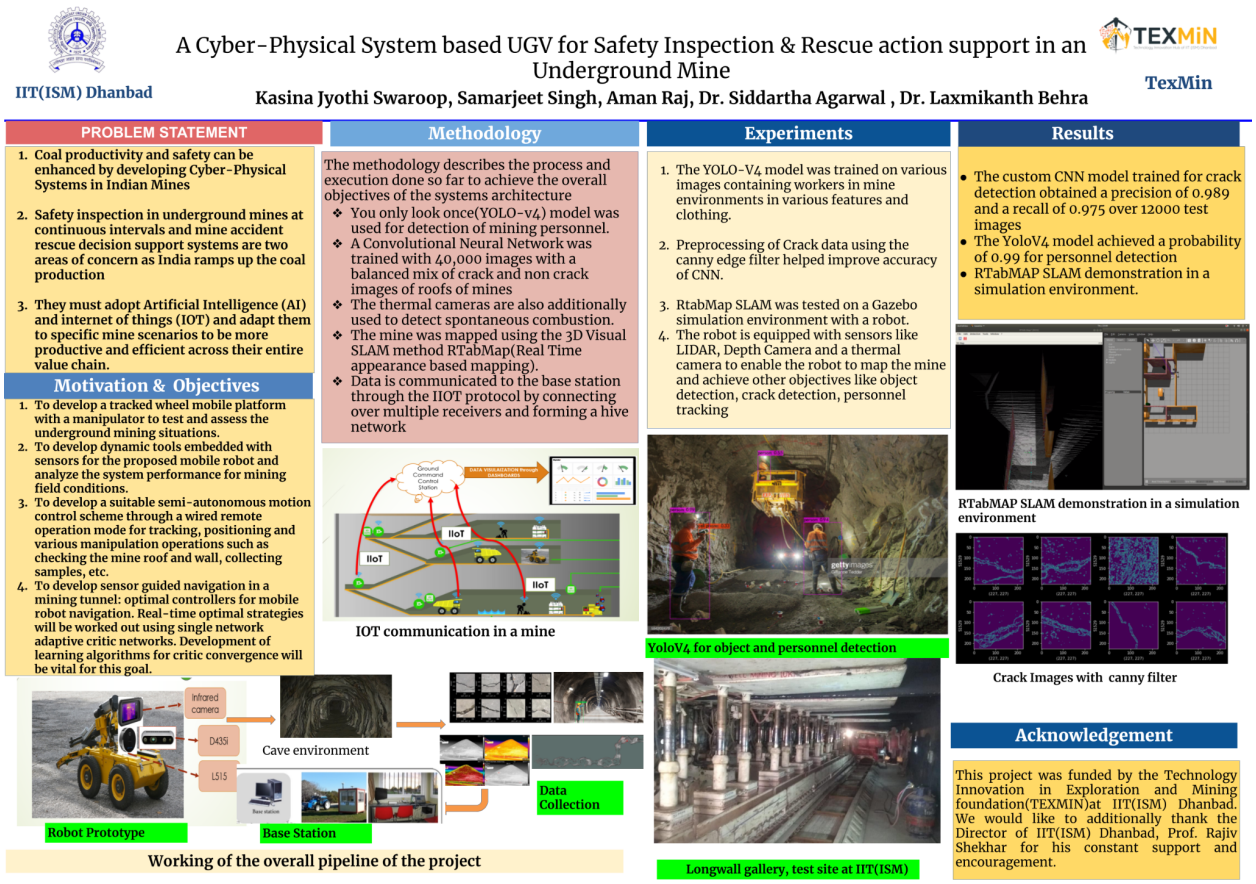


Fig. Communication protocol between Robot and Base station[4]

Base Station setup

A fully functional computer system with Ubuntu 18.04 operating system must be present as a part of the base station to receive and analyze the data in real-time. Apart from this,, the operator at the base station should also form a teleoperation control via ROS, wherein they can control the robot remotely in case of difficult scenarios.

Poster Presentation:



The entire work summarised as a poster was presented as a 10 minute oral presentation at the Research and Industrial Conclave, 2022. Amongst many other teams, our team secured the first prize in this event. We thank Prof. Siddartha Agarwal for actively encouraging us to participate in the event.

Conclusion

The results obtained so far on simulation and in the Longwall Mineare made perfectly end to end, and once the actual systems arrive, with the help of Robot Operating System(ROS), the software integration into the robot will become an easy job. Once the actual robot and the base station are ready and set, with the resources available we can develop the project to the level of Proof of Concept and improve it further.

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