

Minerals Classification from Satellite Image using Deep Learning

Maganti Harish

Department of Electronics and Communication Engineering, VR Siddhartha Engineering College (Autonomous), JNTU Kakinada, India.

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ABSTRACT - Satellite imagery is important in many ways including disaster response, natural calamities, environmental monitoring, defence security to observe the borders. Because the geographic expanses to be covered are great and the analysts available to conduct the searches are few, automation is required. observing and monitoring the minerals based on the climatic conditions and obtaining better results. satellite provides good resolution maps to analyze the obtained data with mapping applications like Gis, Gps, and many experts with high experience in image processing and signal processing

Keywords – Processor,Satellite ,Deep learning,Algorithms

I. INTRODUCTION

Deep learning is a machine learning technique that teaches machines with the help of some codes with the help of computers to do what comes naturally to humans. learn by example. Deep learning technology is key behind driverless trains,buses, enabling them to recognize a stop sign, or to distinguish locations of a particular place with exact accuracy. It is the key to voice control for example with the help of alexa to operate consumer devices like phones, TVs, and other electronic gadgets. Deep learning is the future increasing daily-to- daily basis on the basis of market share.

Existing system: Yet traditional object detection and classification algorithms are too inaccurate and unreliable to solve the problem. Deep learning is a combination of machine learning algorithms that have shown pledge for the

robotization of similar tasks.it has achieved success in image understanding by means of CNN networks.

Proposed system: To develop an Application for minerals classification from Satellite imagery by using Deep Learning Algorithm.Minerals Data visualization is also used to represent the output in the forms of images and charts.

System Requirements

a .Hardware Specifications

- 1. Processor : Intel 7th gen i3
- 2. RAM : 4 GB (min)
- 3. ROM : 80 GB rom
- 4. Key Board : Standard Windows Keyboard
- 5. Mouse : A Standard Mouse
- 6. Monitor : Color monitor (16-bit color)
- b. Software specifications
- 1. Operating Systems:linux/windows
- 2. Simulation Tool : Anaconda with Jupyter Notebook or github

II. METHODOLOGY

This device helps to save the lives of people, who are Suffering with various disease, with this satellite images we can observe various solutions to overcome from this disease. We have presented a deep learning system that classifies objects and facilities in high-resolution multi-spectral satellite imagery. The system consists of an ensemble of CNNs with post-processing neural networks that combine the predictions from the CNNs with satellite metadata.





Fig.1.Data flow Diagram for Minerals classification from satellite image using deep learning

This device comprises of mainly consists of five parts for continuously monitoring they are

- 1. Data Collection and training using Deep Learning Algorithms
- 2. Real Time data gathering and prognostics GUI design
- 3. Applying deep learning algorithm
- 4. Getting the output



collection of data

III. MODULE DESCRIPTION

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Import libraries

Import libraries



Fig.3.Import libraries

Apply deep learning algorithm

deep learning method is very efficient, where experts used to take decades of time to determine the toxicity of a specific structure, but with a deep learning model it is possible to determine toxicity in a very less amount of time (depends on complexity could be hours or days). Deep learning models are able to represent abstract concepts of the input in the multilevel distributed hierarchy. It enables multitask learning for all toxic effects just in one compact neural network, which makes it highly informative.



Getting the output



Fig.4.output

IV.IMPLEMENTATION AND TESTING Unit Testing:

Primary goal of unit testing is to the smallest piece of testable software in the application, isolate it from the remainder of the code, and determine whether it behaves exactly as you expect. Each unit is tested separately before integrating them into modules to test the interfaces between modules. Unit testing has proven its value in that a large percentage of defects are identified during its use.

Integration testing

Testing is done for each module. After testing all the modules, the modules are integrated and testing of the final system is done with the test data, specially designed to show that the system will operate successfully in all its aspects conditions. Thus, the system testing is a confirmation that all is correct and an opportunity to show the user that the system works.

Functional testing:

The final step involves functional testing, which determines whether the software function as the user expected. The end- user rather than the system developer conducts this test most software developer as a process called "Alpha and Beta were testing" to uncover that only the end user seems able to find. The compilation of the entire project is based on the full satisfaction of the end user. In the project, functional testing is made in various forms.

White Box Testing:

White box testing is just the vice versa of

the Black Box testing. They do not watch the internal variables during testing. This gives clear idea about what is going on during execution of the system. The point at which the bug occurs were all clear and were removed.

Black Box Testing

In this testing we give input to the system and test the output. Here I do not go for watching the internal file in the system and what are the changes made on them for the required output.

V. RESULTS & DISCUSSIONS

Efficiency of the Proposed System:

To develop an Application for minerals classification from Satellite imagery by using Deep Learning Algorithm.Minerals Data visualization is also used to represent the output in the forms of images and charts.

Comparison of Existing and Proposed System:

The comparision of existing and proposed system of the project is to automate the detection of minerals classification with help of machine which will be more accurate for classification of Satellite imagery.

Advantages of the Proposed System:

It has achieved astonishing success in object detection and classification by combining large neural network models, called convolutional neural networks (CNNs), with powerful graphical processing units (GPUs).









Fig.7.output

VI. CONCLUSION

We have presented a deep learning system that classifies objects and facilities in highresolution multi-spectral satellite imagery.The system consists of an ensemble of CNNs with postprocessing neural networks that combine the predictions from the CNNs with satellite metadata. Combined with a detection component, our system could search large amounts of satellite imagery for objects or facilities of interest. By monitoring a store of satellite imagery, it could help law enforcement officers detect unlicensed mining operations or illegal fishing vessels, assist natural disaster response teams with the mapping of mud slides or hurricane damage, and enable investors to monitor crop growth or oil well development more effectively.

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