Landsat Image Classification using Convolutional Neural Networks

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Abstract

The report describes a project that aims to use Convolutional Neural Networks (CNNs) to identify locations for mineral deposits on the earth's surface using the dataset from NASA's Landsat program and a dataset of known mineral deposits. The goal is to minimize the environmental impact caused by mineral extraction, which is harmful to the environment and human health. The Landsat dataset is preprocessed by downsampling the images and labeling them using a K-D Tree Search Algorithm. The labeled images are sorted into location buckets and ocean masking is performed to ensure that the CNN built is not predicting whether the image is land or ocean. The images at each location are then sorted by degree of cloud cover, allowing the selection of training images with fewer clouds. Once the images are preprocessed, they are split into training and testing sets with balanced classes for binary classification, or with equivalent distributions for regression. Two types of CNN models, binary classification, and regression, were implemented to determine the land's suitability for mineral extraction. Several different model architectures were investigated to achieve high accuracy, and a preliminary baseline was obtained for evaluation purposes. The trained models obtained an accuracy of 73% on the binary classification problem, and a MAE of 0.117 on the regression problem; these values were both significant improvements on the baselines. Training on more powerful hardware and using the full-resolution images may produce further improvements.

1 Introduction

Convolutional Neural Networks (CNNs) have proved to be highly effective in real-life applications, especially in image classification, as they can extract features from patterns without being affected by their locations [1]. As such, the dataset from NASA's Landsat program contained over 3 million earth observation scenes. This dataset was used alongside a dataset containing the world's known mineral deposits on Earth. The goal of using CNNs to determine locations for mineral deposits. A problem in natural resource extraction is that it is extremely harmful to the environment and human health, however, it is crucial for construction, manufacturing, and energy production. Many countries generate significant revenue from mineral resource extraction, therefore it is a field that will continue to thrive. Petroleum and gas production is required for mineral extraction and contributes to surface and groundwater pollution, erosion, and sedimentation. Using CNNs and the NASA Landsat dataset to identify areas with rich mineral deposits for targeted exploration and extraction can help minimize environmental impact.

The primary objective of the project was to create a supervised machine learning algorithm, CNNs, that could accurately predict the land's suitability for mineral extraction. By identifying the exact locations and types of minerals present in the land, the amount of pollution caused by the extraction of waste rock and the chemical process of separating the desired minerals from the waste rock could be significantly reduced [2]. The Landsat dataset contains extensive images of Earth, where the images were cross-referenced for existing resource deposits to predict mineral deposit locations.

2 Data Processing

The Landsat dataset was preprocessed before training the CNN. The Landsat dataset chosen was Landsat 4 - band 7, which used Thematic Mapper sensors to capture the images. This means the images were shortwave infrared, and sensitive to hydrothermally altered rocks, associated with mineral deposits. The images were taken from the vertices of a 2x2 latitude-longitude grid, all approximately 7500x7500 pixels in a single colour channel. The mineral deposit dataset comprised about 350,000 known public mineral deposits and the minerals present. This data was verified by manual inspection of random records and is therefore incomplete.

Figure 1: Example images from Landsat 4 Band 7.

Figure 2: Mineral deposit dataset visualization on world map.

In the data preprocessing pipeline, the images were downsampled to allow for training on the authors' personal computers using consumer GPUs. Since 7500x7500 pixels are too large, the Python library ImageMagick is used to downsample the images to 512x512 pixels. The sampling is used because it is the fastest, however, it has the highest information loss for the images. Each image takes approximately 6 seconds to process through the acquisition pipeline, and a total of 75 hours are needed to process all of the images in the dataset. The metadata file is then downloaded, which contains additional information about the images, such as the location and other identifying details.

Figure 3: Label Creation.

Figure 4: Step by step data preprocessing pipeline.

A K-D Tree Search Algorithm was used to label the images according to the mineral deposit dataset, since KD trees greatly accelerate queries on spatial data [3]. In the label creation, the deposit locations are first placed in a KD tree. Then for each image, the enclosing circle of the image is obtained, the KD tree is queried for the subset of deposits present in the enclosing circle, and a convex polygon test is used to identify which of those deposits lie within the image. This method was used since it supported queries on the irregular regions shown in Landsat images, which are neither axis-aligned nor perfectly rectangular. For binary classification, the images are labeled 1 or 0 depending on the presence or absence of mineral deposits. For regression, the images are labeled according to a richness score in a range of 0 to 1. The richness score is computed as the log transform of the absolute count of deposits in the image, normalized to the range [0, 11]; the log transform was used to reduce the skew of the regression values.

Once the images are labeled using the KD tree search algorithm, the images are then sorted into buckets based on their locations. There are approximately 6000 unique location buckets. This allows us to ensure that images of the same location do not end up in the training and test sets simultaneously. The images containing the ocean are removed. To perform the ocean masking, the Python library Geopandas is used to load the geospatial data for the borders of every country. Each image's center point is tested for where it belongs in the polygons, to determine where the image belongs in each country. This ensures that the CNN built is not predicting whether the image is land or ocean. Finally, the images at each location are sorted by average pixel brightness, which effectively sorts by degree of cloud cover. This permits the selection of images having less cloud cover, as the clouds can interfere with predicting if the land contains minerals.

Once the images have labels and have been preprocessed, the images are split 80/20 into training and testing sets with balanced classes for binary regression, or equivalent distributions for regression. All pixel brightnesses were normalized to the range [0, 1].

3 Convolutional Neural Networks

The chosen machine learning algorithm was a CNN using binary classification and a CNN using regression. Tuning was performed in two stages: first the architecture was tuned, then the hyper-parameters were tuned. Several different model architectures were investigated to achieve high accuracy. During tuning, the models were varied over two architectural characteristics: the size of the convolutional network and the size of the dense network. Each network was made to be large, medium, or small, as a label for each. This helped determine whether the problem benefited from learning highly abstract patterns, such as deep and narrow models, or staying closer to the source data with shallow and wide models. The architecture producing the greatest accuracy or lowest error was then selected and subjected to hyperparameter tuning.

The preliminary baseline, without any optimizations or hyperparameter tuning, and with the training labels randomized, returned results for binary classification of 50% value accuracy, and the regression produced a mean absolute error (MAE) of 0.127, which is a measure of the difference between the predicted and actual values. A lower MAE indicates better accuracy in predicting the richness score of the mineral deposits. Obtaining a baseline was an important step in evaluating the performance of the models, as it helps determine if any additional efforts to optimize the model are improving its performance.

The CNNs were trained on samples drawn from the unique location buckets over land, and each with a minimum of cloud cover. For training the CNN, a test bench was created with a setup of Tensorflow GPU support, to speed up the model training times.

4 Problem Definition

The text must be confined within a rectangle 5.5 inches (33 picas) wide and 9 inches (54 picas) long. The left margin is 1.5 inch (9 picas). Use 10 point type with a vertical spacing (leading) of 11 points. Times New Roman is the preferred typeface throughout, and will be selected for you by default. Paragraphs are separated by ½ line space (5.5 points), with no indentation.

The formatting instructions contained in these style files are summarized in

The paper title should be 17 point, initial caps/lower case, bold, centered between two horizontal rules. The top rule should be 4 points thick and the bottom rule should be 1 point thick. Allow ¼ inch space above and below the title to rules. All pages should start at 1 inch (6 picas) from the top of the page.

For the final version, authors' names are set in boldface, and each name is centered above the corresponding address. The lead author's name is to be listed first (left-most), and the co-authors' names (if different address) are set to follow. If there is only one co-author, list both author and co-author side by side.

Please pay special attention to the instructions in Section 6 regarding figures, tables, acknowledgments, and references.

5 Related Work

All headings should be lower case (except for first word and proper nouns), flush left, and bold.

First-level headings should be in 12-point type.

5.1 Headings: second level

Second-level headings should be in 10-point type.

5.1.1 Headings: third level

Third-level headings should be in 10-point type.

Paragraphs There is also a `\paragraph` command available, which sets the heading in bold, flush left, and inline with the text, with the heading followed by 1 em of space.

6 Citations, figures, tables, references

These instructions apply to everyone.

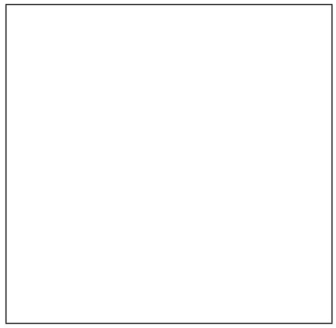

Figure 1: Sample figure caption.

6.1 Citations within the text

The `natbib` package will be loaded for you by default. Citations may be author/year or numeric, as long as you maintain internal consistency. As to the format of the references themselves, any style is acceptable as long as it is used consistently.

The documentation for `natbib` may be found at

```
http://mirrors.ctan.org/macros/latex/contrib/natbib/natnotes.pdf
```

Of note is the command `\citet`, which produces citations appropriate for use in inline text. For example,

```
\citet{hasselmo} investigated\dots
```

produces

> Hasselmo, et al. (1995) investigated…

If you wish to load the `natbib` package with options, you may add the following before loading the `neurips_2020` package:

```
\PassOptionsToPackage{options}{natbib}
```

If `natbib` clashes with another package you load, you can add the optional argument `nonatbib` when loading the style file:

```
\usepackage[nonatbib]{neurips_2020}
```

As submission is double blind, refer to your own published work in the third person. That is, use "In the previous work of Jones et al. [4]," not "In our previous work [4]." If you cite your other papers that are not widely available (e.g., a journal paper under review), use anonymous author names in the citation, e.g., an author of the form "A. Anonymous."

6.2 Footnotes

Footnotes should be used sparingly. If you do require a footnote, indicate footnotes with a number[1] in the text. Place the footnotes at the bottom of the page on which they appear. Precede the footnote with a horizontal rule of 2 inches (12 picas).

Note that footnotes are properly typeset *after* punctuation marks.[2]

6.3 Figures

All artwork must be neat, clean, and legible. Lines should be dark enough for purposes of reproduction. The figure number and caption always appear after the figure. Place one line space before the figure

[1] Sample of the first footnote.

[2] As in this example.

Table 1: Sample table title

Part		
Name	Description	Size (μm)
Dendrite	Input terminal	$\sim$100
Axon	Output terminal	$\sim$10
Soma	Cell body	up to 10^6

caption and one line space after the figure. The figure caption should be lower case (except for first word and proper nouns); figures are numbered consecutively.

You may use color figures. However, it is best for the figure captions and the paper body to be legible if the paper is printed in either black/white or in color.

6.4 Tables

All tables must be centered, neat, clean and legible. The table number and title always appear before the table. See Table 1.

Place one line space before the table title, one line space after the table title, and one line space after the table. The table title must be lower case (except for first word and proper nouns); tables are numbered consecutively.

Note that publication-quality tables *do not contain vertical rules.* We strongly suggest the use of the `booktabs` package, which allows for typesetting high-quality, professional tables:

`https://www.ctan.org/pkg/booktabs`

This package was used to typeset Table 1.

7 Final instructions

Do not change any aspects of the formatting parameters in the style files. In particular, do not modify the width or length of the rectangle the text should fit into, and do not change font sizes (except perhaps in the **References** section; see below). Please note that pages should be numbered.

8 Preparing PDF files

Please prepare submission files with paper size "US Letter," and not, for example, "A4."

Fonts were the main cause of problems in the past years. Your PDF file must only contain Type 1 or Embedded TrueType fonts. Here are a few instructions to achieve this.

- You should directly generate PDF files using `pdflatex`.
- You can check which fonts a PDF files uses. In Acrobat Reader, select the menu Files>Document Properties>Fonts and select Show All Fonts. You can also use the program `pdffonts` which comes with `xpdf` and is available out-of-the-box on most Linux machines.
- The IEEE has recommendations for generating PDF files whose fonts are also acceptable for NeurIPS. Please see `http://www.emfield.org/icuwb2010/downloads/IEEE-PDF-SpecV32.pdf`
- `xfig` "patterned" shapes are implemented with bitmap fonts. Use "solid" shapes instead.
- The `\bbold` package almost always uses bitmap fonts. You should use the equivalent AMS Fonts:

  ```
  \usepackage{amsfonts}
  ```

  followed by, e.g., `\mathbb{R}`, `\mathbb{N}`, or `\mathbb{C}` for $\mathbb{R}$, $\mathbb{N}$ or $\mathbb{C}$. You can also use the following workaround for reals, natural and complex:

```
\newcommand{\RR}{I\!\!R} %real numbers
\newcommand{\Nat}{I\!\!N} %natural numbers
\newcommand{\CC}{I\!\!\!\!C} %complex numbers
```

Note that `amsfonts` is automatically loaded by the `amssymb` package.

If your file contains type 3 fonts or non embedded TrueType fonts, we will ask you to fix it.

8.1 Margins in LaTeX

Most of the margin problems come from figures positioned by hand using `\special` or other commands. We suggest using the command `\includegraphics` from the `graphicx` package. Always specify the figure width as a multiple of the line width as in the example below:

```
\usepackage[pdftex]{graphicx} ...
\includegraphics[width=0.8\linewidth]{myfile.pdf}
```

See Section 4.4 in the graphics bundle documentation (`http://mirrors.ctan.org/macros/latex/required/graphics/grfguide.pdf`)

A number of width problems arise when LaTeX cannot properly hyphenate a line. Please give LaTeX hyphenation hints using the `\-` command when necessary.

Broader Impact

Authors are required to include a statement of the broader impact of their work, including its ethical aspects and future societal consequences. Authors should discuss both positive and negative outcomes, if any. For instance, authors should discuss a) who may benefit from this research, b) who may be put at disadvantage from this research, c) what are the consequences of failure of the system, and d) whether the task/method leverages biases in the data. If authors believe this is not applicable to them, authors can simply state this.

Use unnumbered first level headings for this section, which should go at the end of the paper. **Note that this section does not count towards the eight pages of content that are allowed.**

Acknowledgments and Disclosure of Funding

Use unnumbered first level headings for the acknowledgments. All acknowledgments go at the end of the paper before the list of references. Moreover, you are required to declare funding (financial activities supporting the submitted work) and competing interests (related financial activities outside the submitted work). More information about this disclosure can be found at: `https://neurips.cc/Conferences/2020/PaperInformation/FundingDisclosure`.

Do **not** include this section in the anonymized submission, only in the final paper. You can use the `ack` environment provided in the style file to autmoatically hide this section in the anonymized submission.

References

References follow the acknowledgments. Use unnumbered first-level heading for the references. Any choice of citation style is acceptable as long as you are consistent. It is permissible to reduce the font size to `small` (9 point) when listing the references. **Note that the Reference section does not count towards the eight pages of content that are allowed.**

[1] Alexander, J.A. & Mozer, M.C. (1995) Template-based algorithms for connectionist rule extraction. In G. Tesauro, D.S. Touretzky and T.K. Leen (eds.), *Advances in Neural Information Processing Systems 7*, pp. 609–616. Cambridge, MA: MIT Press.

[2] Bower, J.M. & Beeman, D. (1995) *The Book of GENESIS: Exploring Realistic Neural Models with the GEneral NEural SImulation System.* New York: TELOS/Springer–Verlag.

[3] Hasselmo, M.E., Schnell, E. & Barkai, E. (1995) Dynamics of learning and recall at excitatory recurrent synapses and cholinergic modulation in rat hippocampal region CA3. *Journal of Neuroscience* **15**(7):5249-5262.