Assignment 4 – Minor Thesis

SIT792 Minor Thesis

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Abstract

The construction of a gold mine is a complex process involving expertise from many disciplines. The exploration stage can take between 1 and 10 years and on average it takes between 10 and 20 years before a mine is considered productive (World Gold Council, 2019). Using Design Science Research Methodology (DSRM), this study constructs a prototype 'You Only Look Once' (YOLO) object detection classifier to consider its suitability for applying deep learning on LandSat Satellite imagery to aid gold prospecting. With LandSat images of 'Doug Strone Outdoor Press – Gold & Relic Map' gold nugget discovery locations, YOLO is able to output confidence ratings for geological objects in natural scene images of known gold nugget sites which can then be compared to new prospecting locations. Landsat8 remote sensing imagery is able to illustrate the existence of hills or mountains near a known gold discovery site but does not have the adequate focus to support geological object detection.

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Chapter 1

Introduction to the field of research

In 2019, gold production in Australia hit a 20-year high (Mining Technology, Jan 2019), the Victorian Government Minister for Resources (Mar 2019, Media Release) extended mining licences at Victoria's largest mines in Stawell and Fosterville till 2035 stating "Victoria's wealth was built on gold mining and the industry remains integral to creating regional jobs." In 2018, $15 million worth of gold was discovered 500m below the surface in a 3m squared area and lifted to the surface in 4 days at the Western Australia Beta Hunt Mine in the Kambalda mining district. At the time of the discovery, the mine was owned by Canadian company RNC Minerals and was up for sale, since the discovery, RNC has opted to not sell the mine that was originally opened to mine nickel (ABC News, Sep 2018).

Whilst finding gold can be the result of pure luck, for example finding nuggets in creeks and rivers, searching for exposed minerals and deciding where to start mining is the act of prospecting performed by geologists. Gold can be found at the surface or deeper underground. Depending on digging samples, a company will decide whether it is profitable to construct a mine for further mining exploration (William Harris, n.d.). To assist with prospecting, geologists began using aerial photography and "remote sensing" via cameras held outside of airplane windows dating back to the 1940's (Gabr, Ghulam, Kusky, 2010, pg. 1). Today, satellites can provide geologists with land surface photography and remote sensing information about the characteristics of the land, by measuring reflected and emitted radiation (US. Dept. of the Interior, n.d.).

Key related work

In their research paper titled "A Critical Analysis of Gold Prospecting Methods" (Sailou, Huang, Feb 2020) critically analysed both traditional (gold panning, dry washing and biological prospecting) and modern methods (geochemical and geophysical) for gold prospecting. The research concluded that whilst the modern practises explain a resurgence of gold mining from the 1950's and onwards, these modern methods are still inconsistent and ineffective in cost and across the world. Further research may assist in improving the prospecting of minerals.

Unrelated to gold mining, in 2015 via the University of Washington, Allen Institute for AI and Facebook AI Research developed YOLO, as a new approach to object detection (Redmon, Divvala, Girshick, Farhadi, 2015, pg.1). YOLO software was released as open source CNN (Convolutional Neural Networks) software designed specifically for detecting objects in images, movies and live streams. The

YOLO algorithm is efficient and effective as it creates grids in the images and uses regression probability to detect objects embedded in images.

Key aims – Thesis contribution

The aim of this research proposal is to leverage YOLO, or an ensemble with other algorithms, to train and fine-tune a predictive model to identify key minerals in existing gold mine geology photography. By developing and training this model, predictions can be applied to new satellite photography and remote sensing topology combinations, to identify mineral objects with a detailed multiple regression analysis with the probability of gold deposits and likely locations. Unlike traditional binary neural network classifiers, a YOLO based predictive model will be able to illustrate many object classes and instances detected within a single satellite image.

This thesis aims to provide gold prospectors with a competitive advantage to better understand the geological surface of existing gold nugget discovery locations, and consequently compare and prioritise new gold prospect sites.

The research problem and key research questions

The research problem is that successful outcomes in gold prospecting are still very much uncertain, despite thousands of years of gold exploration in human civilisations.

1. Can prospecting be more successful by usage of deep learning on satellite imagery?
2. Can YOLO object detection benefit amateur prospectors, geologists and mining companies in comparing and best choosing prospecting sites from LandSat and LandSat8 Satellite images?

The research methodology

Design Science Research Methodology

The DSRM (Design Science Research Method) will be employed for this thesis topic. In 2015, a study titled 'When is a problem a design science problem?' listed 3 guidelines for when a problem meets the DSRM requirement (R Gleasure, 2015):

1. when the prescriptive aspect of the research problem is less mature than the analytical, explanatory, or predictive aspect.
2. when an opportunity arises to engage with a class of design problems where effective existing solutions do not yet exist.
3. when important elements of a system may only become visible through the act of design.

The research problem is determining if the YOLO object detection algorithm is a suitable for identifying distinct object classes in satellite imagery to improve the efficiency of prospecting meets each of these 3 guidelines. There is no known universal object detection predictive model to classify object classes in satellite imagery, and as such, to best answer the research question, a prototype predictive model is to be constructed and evaluated.

This research proposal has documented the "awareness of a problem" and put forward a "suggestion" for creating a fine-tuned predictive model to be applied to satellite images. A predictive model prototype will be designed and developed for evaluation and relevant conclusions and circumscriptions will be drawn when the prototype is tested against new satellite images. Satellite images can be obtained from the Landsat Satellite under an open source licence.

YOLO Real-Time Object Detection

In his 2017 Ted Talks presentation titled 'How computers learn to recognize objects instantly', Joseph invites his audience to use his free open source software, 'Anyone can take it and build something with it. So now the rest is up to all of you and people around the world with access to this software, and I can't wait to see what people will build with this technology.'

Further explanations on YOLO software can be found at the following URL; https://github.com/pjreddie/darknet/wiki/YOLO:-Real-Time-Object-Detection

Whilst it is feasible to purchase amateur gold metal detectors and to manually dig up surfaces in Australian national parks, with a $25 gold licence, evaluation of the predictive gold prospecting model will be consistently explaining existing known gold mines. What are the common combinations of minerals and what proportions of these minerals could be expected to appear in a zone known to have had gold deposits? Given that Victoria has a rich history in gold mining and Western Australia has active gold discoveries, this project will focus on exploring satellite images of these 2 states of Australia.

Chapter 2

Literature Review Introduction

Prospecting for valuable metals can be aided with geophysics. In a series of University of British Columbia lectures for the subject "Environmental, Geotechnical and Exploration Geophysics" made available as open-source material, the lecturer summarises his subject material with a statement "use geophysics before random digging" (D Oldenburg, 2016). Modern geophysics methods include surveying tools that leverage electromagnetics to detect and measure "chargeability" readings from the surface of the earth to predict the underlying presence of minerals such as quartzites and pyrite and other minerals that are commonly associated with gold. Satellite imagery for prospecting in inaccessible regions is to be noted by mining companies for the early stages of exploration (Pour et al. 2019).

The use of object detection over satellite imagery for the purpose of gold mine exploration can address and improve the efficiency of many phases in the near 1 to 10-year process of establishing a gold mine. The beginning of gold mine exploration starts with a search for minerals commonly associated with gold deposits such as silver and copper contained in ore found at the Earth's surface (World Gold Council, 2019). Ore is described as a deposit in the Earth's crust in which the most valuable ore deposits are those that contain metals crucial to industry and trade, like copper, gold and iron (National Geographic, 2011). Whilst less than 0.1% of prospected sites lead to productive mines, there are many considerations of where to establish a future gold mine other than the results of geophysical surveys that determine the volume of gold deposits. Some of those considerations are the impacts to local communities, environments and nearby access to water to assist with mining operations. Politics is also an obstacle in gold mine exploration. A single gold mine prospect in Sekotong, Indonesia, has been identified as a site that could sustain decades of mining productivity, however the regional government is actively limiting access to this part of the country (Y Palimbong et al, 2020).

The exploration of other valuable minerals can also benefit from the usage of satellite imagery in the early stages of exploration. An emerging mining industry in Western Australia and other parts of the world is Lithium. This mineral is commonly associated with other minerals that are potentially found at the Earth's surface (Sweetapple, Tassios, Body, 2015).

Key research areas reviewed

Usage of computing algorithms on satellite imagery in the field of prospecting

In 2019 an international research project assisted by institutions and universities from 7 countries, set 3 objectives in analysing satellite images from the Landsat-8, ASTER, and WV-3 satellites (Pour et al. 2019):

1. Map minerals associated with copper-gold mineralisation.
2. Implement the algorithms Directed Principal Components Analysis (DPCA), Linear Spectral Unmixing (LSU), Adaptive Coherence Estimator (ACE) for mineral detection and analysis.
3. Establish use of satellite imagery as a valuable and cost-effective approach compared to geophysical and geochemical techniques.

With an overall accuracy between 65% and 77% in detecting minerals from the satellite images the research concluded that mining companies need to use satellite image analysis for mineral prospecting before investing in costly geophysics field work.

There exist positive trends in lithium exploration in the present day, driven primarily by the usage of lithium in rechargeable batteries. In a 2017 survey published by the United States Geological Survey (USGS), Australia ranked 3rd place in total volume of lithium resources (David Champion, Geoscience Australia, 2018). In 2020 an international research project assisted by institutions and universities from 3 countries trialled satellite (ASTER, Landsat-8, and Sentinel-2) imagery analysis in the exploration of lithium, addressing 4 topics (Cardoso-Fernandes et al. 2020):

1. The achievements made in lithium exploration using remote sensing
2. Weaknesses of the approaches
3. How to overcome those difficulties
4. Expected research perspectives

The research performed trials of the algorithms Support Vector Machine (SVM) and Random Forests (RF) algorithms for image classification. Image classification accuracy rates between 97.70% and 98.54% were obtained in detecting lithium pegmatite mapping. Despite high accuracy levels, the research admitted the occurrence of over-fitting and false positives. In conclusion, the paper stated the constant development in machine learning algorithms offered unlimited possibilities to be explored.

In 2019 a University of Western Ontario research paper was published with the task of autonomously classifying rocks in real-time. In addition to the benefits of classifying rocks without the need of a laboratory or performing the task over difficult terrain such as another planet, the research achieved 100% accuracy by using Convolutional Neural Network (CNN) algorithms (A D Pascual, 2019). The objectives were:

1. Explore the use of CNN to classify rocks
2. Classify rocks in natural images so a tablet device could be used to classify rocks in real-time

The research concluded that CNN have superior performance over traditional methods in classifying clean images of rocks. The research also concluded that rock classification models could be ported to mobile devices and future work would ideally enable any user with a mobile tablet device to classify natural images of rock with immediate feedback.

Summary of key research

Table 1 Authors, algorithms and classification accuracy

Authors	Algorithms	Accuracy
(Pour et al. 2019)	Directed Principal Components Analysis (DPCA), Linear Spectral Unmixing (LSU), Adaptive Coherence Estimator (ACE)	65% - 77%
(Cardoso-Fernandes et al. 2020)	Support Vector Machine (SVM), Random Forests (RF)	97.70% - 98.54%
(A D Pascual, 2019)	Convolutional Neural Network (CNN)	100%

Methodologies and methods being used to answer challenges / questions

Convolutional neural network algorithms for object detection in real-time

In 2015 the first paper on "You Only Look Once" YOLO CNN algorithm was published. YOLO was presented as a new approach to object detection, a single neural network predicting bounding boxes and class probabilities as a regression problem from a single image in 1 evaluation (Redmon et al. 2015). The paper concluded that their new approach was ideal for applications with a requirement for fast and robust object detection. In 2016, a follow up research paper on YOLO was published, claiming that the second version of the YOLO algorithm could detect up to 9000 object categories whilst still running in real-time (Redmon, Farhadi, 2016). In 2018, a 3rd version of YOLO was released, the most recent updates focused on improving the algorithm's accuracy without compromising its speed (Redmon, Farhadi, 2018).

In 2016 a research paper explored the feasibility of a mobile device with a GPU executing CNN algorithms for computer vision tasks of object detection. With models trained on servers, and mobile devices constantly increasing their computing resources and quality of cameras, could they eventually execute predictive computer vision tasks? (Rallapalli et al. 2016). The study focused on the newly introduced YOLO algorithm because it was able to visually outline a box around the object that was detected. The results of this research were inconclusive. As future CNN's were likely to require more memory as too were mobile phones likely to be developed with more resources to meet that excessive memory requirement. The paper acknowledged that there were trade-offs to consider but also asked the question as to how likely it was that mobile devices would be use a CNN algorithm against a continuous live video stream.

In 2019 a research paper explored the YOLO CNN algorithm for real-time object detection, this time from perspective of using it in conjunction with mobile devices attached to an unmanned aerial vehicle (UAV), alternatively known as a drone. YOLO was described as the representative one-shot object detection method specialised for high detection speed and relatively high levels of accuracy, making it very suitable for real-time applications. The paper explained that YOLO was an exceptional CNN algorithm as it analyses still images and video frames in a grid format, unlike other CNN's (Li, Sun, Cai, 2019). The research successfully completed a trial of "tiny YOLO", a refined version of YOLO for real-time object detection on mobile devices. The trial was implemented on an Apple iPhone version 7 utilising "CoreML" an Apple framework/API that allows machine learning models to run on the iPhone's CPU, GPU or Neural Engine (M Hollemans, 2019). The study suggested an improvement in performance with new versions of Apple iPhone.

There was more research in 2019 that explored the YOLO CNN algorithm for real-time object detection on the Apple iPhone. A research paper leveraging the Apple iPhone "neural engine", dual processing units embedded in the iPhone hardware that also included a Graphical Processing Unit (GPU), asked 2 questions (J Güven, 2019).

1. What is the practicality of detecting objects such as doors in real-time on a mobile device?
2. How can model tuning (hyperparameters, etc.) improve speed and accuracy of YOLO CNN?

Other CNN algorithms such as "MobileNets" were considered but based on their test results and the consistent findings of other research papers, YOLO obtained the best results for speed and accuracy. Jakup Güven also preferred the "tiny YOLO" version of YOLO due to its suitability for real time video object detection. False positives were encountered due to overfitting in model training, though this problem was corrected by adding new training object classes. A trade-off was also discovered between object detection accuracy and speed.

The research concluded with confirmation of technical viability and feasibility in integrating mobile devices with CNN algorithms. The research paper made many suggestions for fine-tuning a CNN based application on a mobile device but also stated that further research into hyperparameter tuning was necessary.

In 2020 a research paper optimized YOLO hyperparameters for the task of detecting vehicle licence plates with complex environmental scenarios such as rain, dust and shadows. The research significantly improved their recall and precision ratios by using different quality types of cameras (Al-Qudah, Suen, 2020). Interesting comparisons were obtained with the different image resolutions, including the Apple iPhone versions 6 and 7 Plus. Image resolution dictated the optimum number of training iterations. The problem of 'false positives' emerged and further research was suggested to apply object detection in the task of saving lives in search and rescue.

Summary of methodology research

Table 2 Authors, algorithms and challenges

Authors	Algorithms	Challenges
Rallapalli et al. 2016	You Only Look Once (YOLO)	Hand-held device performance, accuracy vs. speed trade-off
Li, Sun, Cai, 2019	You Only Look Once (YOLO)	Hand-held device performance, accuracy vs. speed trade-off
J Güven, 2019	You Only Look Once (YOLO)	Overfitting/false positives, hyperparameter tuning
Al-Qudah, Suen, 2020	You Only Look Once (YOLO)	Overfitting/false positives, image resolution

Literature Review Conclusion

The usage of satellite imagery for mineral exploration brings cost benefits to mining companies as well as providing visibility in inaccessible regions of the world. The highest levels of accuracy obtained via usage of Convolutional Neural Networks based algorithms applied to satellite images as summarised from 3 studies are in table 1. In addition to improving gold mine exploration from satellite imagery, a CNN based algorithm YOLO can perform real-time object detection from a mobile hand-held device that have useful purpose for gold prospecting, in scenarios such as identifying mineral types without needing to transport rocks to a laboratory. As summarised in table 2, whilst there exist memory constraints with hand-held devices, recent versions Apple iPhone have hardware capable of supporting the execution of models and applications that can perform real-time object detection. False positive object detection from training overfitting was documented as a technical challenge in 2 studies using the YOLO algorithm, in 1 of the studies this challenge was overcome by introducing new object categories into the training set.

Chapter 3

Problem Analysis

Creating a predictive model

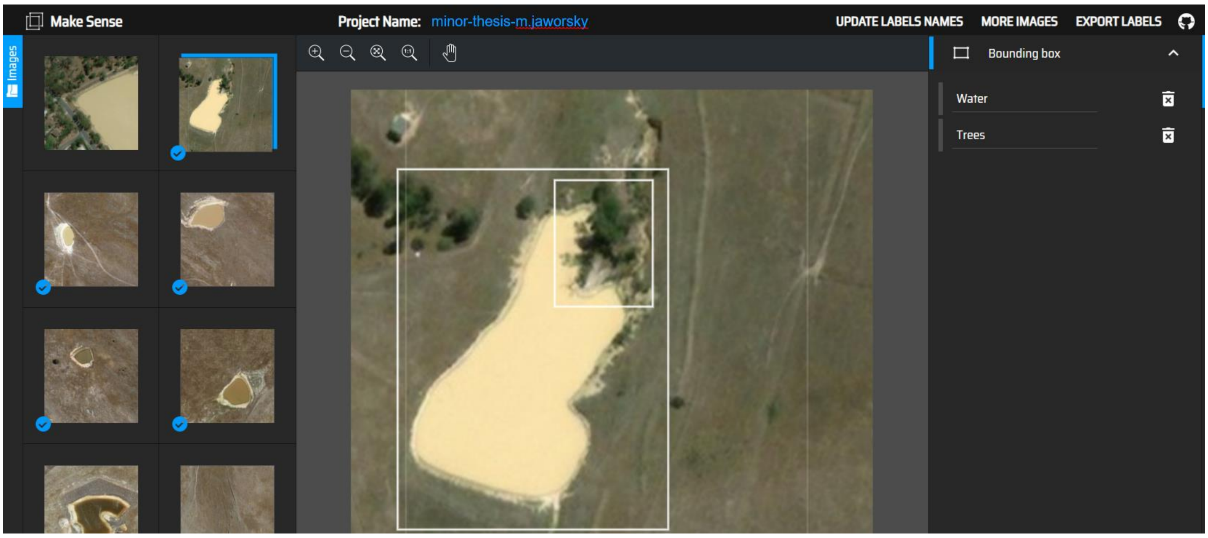
A 2019 research paper using YOLO to perform object detection in videos of traffic, documented the following steps in creating their predictive model (S Luo, C Xu, H Li, 2019).

- Image annotation (object labelling)
- Image resizing (416 x 416 pixels)
- Split images into training (90%) and test sets (10%)
- Split second batch of images into training (80%) and validation sets (20%)
- Obtain GPU for backpropagation training of the neural network
- Organise training dataset into batches of 64
- Refine hyperparameter settings to improve prediction outcomes

A YOLO neural network model has a predefined set of layers, weights, hyperparameters and sample class objects. The intent of this study is to determine if the YOLO algorithm is suitable for object detection in using satellite imagery for prospecting precious mineral deposits. Furthermore given that the YOLO default object classes are not specialised geological objects visible in satellite imagery, the default YOLO hyperparameter settings will also be explored to determine if the YOLO algorithm can be tuned to optimise the model performance for the purpose of prospecting.

The LandSat satellite data products are free to be searched, downloaded and are practical for the purposes of creating image datasets for training, testing and validation. Using a standard image editor satellites can be resized or cropped to the default image input size of 416 x 416 pixel size.

Image annotation is the process of labelling each image in the training sets with the object classes that are present in each image and what the pixel boundaries are for those objects. Splitting images into training and test sets first requires a decision on the number of images to obtain and label. As training batches are by default in sizes of 64, the same number of images is also very practical to train and test hyperparameter values. Less than 64 images in a training set can be inadequate in improvement of the neural network weights when performing backpropagation training iteration epochs. Training sets much larger than the default batch size of 64 will consume large amounts of memory and slow down the training process.



Screenshot 1 – makesense.ai web portal allows users to upload training dataset images, label the objects in each of the training images and export the annotated CSV files that explain where each object class is located.

The Google Colab Research developer environment is particularly useful as developers can gain access to a 12GB GPU. Google researchers claim that GPUs can speed up common operations [in comparison to being performed on a CPU] by a factor of 5x to 50x (V Vanhoucke, A Senior, M Z. Mao, 2011). In this study, Google Colab developer environment GPU managed to perform approximately 1000 epochs on a batch size of 64 in an hour, compared to 100 epochs on a smaller batch size in 8 hours on CPU only. This was a factor improvement in excess of 80x.

As a guide to how many iterations are required to create an accurate object detection classification model, it is suggested once training reaches an average (classification) loss of below 0.060730, you can stop training (N Tijtgat, 2017). However, achieving this average loss value is a not fate accompli, as the maximum batch iterations will end the training process independently of what the average loss value is.

The following hyperparameter values exist in YOLO (version 3) configuration files and have default values:

- Batch Size: Insufficient training sample set size will not be able to improve a model over many training iterations. A symptom of an inadequate training set can be identified in training iterations that report a loss value of “-nan”. Alternatively, excessive training set sizes can reach hardware memory limits during the training exercise.
- Subdivisions: If the total training set size is larger than the available memory size, training iterations will need to be performed with smaller divisible batch sizes to avoid memory

constraints. These smaller batches are referred to as subdivisions. A convenient number of subdivisions can corelate to the number of image classes in a training set.

- Maximum Batches: Training will end when the maximum batches number of training iterations have been completed. When a YOLO model performs object detection, a level of confidence is logged, and users can gauge whether the model performance is fit for purpose.
- Width [Height]: Training set image input pixel width [height]. If training set image pixel sizes are not uniform, the training function will resize the images. Whilst a uniform training set image size can achieve more accurate results with a smaller training set, it is important to note that for the model to maintain the same level of accuracy over a test set, the test set will also need to maintain those image pixel widths and heights. To build a powerful image classifier image augmentation is usually required to boost the performance of deep networks (S Lau, 2017).
- Angle: Data augmentation - random rotation of image during training (A Bochkovskiy, 2019).
- Saturation: Data augmentation – random change of saturation during training (A Bochkovskiy, 2019).
- Exposure: Data augmentation – random change of brightness during training (Alexey AB, 2019).
- Hue: Data augmentation – random change of colour during training (A Bochkovskiy, 2019).
- Blur: Data augmentation – random blurred effects during training (A Bochkovskiy, 2019).
- Min_Crop [Max_Crop]: Data augmentation – minimum [maximum] size of a randomly cropped image (A Bochkovskiy, 2019).
- Aspect: Data augmentation – classification aspect ratio change during training (A Bochkovskiy, 2019).
- Jitter: Data augmentation – random change of image size and aspect ratio (A Bochkovskiy, 2019).
- Adam: Optimiser choice – set to 1 to use Adam optimiser, default = 0.

The following 3 YOLO hyperparameter configuration values are generic hyperparameters configurable for all neural network algorithm model training:

- Momentum: is a method that helps accelerate Stochastic Gradient Descent in the relevant direction and dampens oscillations (S Ruder, 2016).
- Decay: Regularisation parameter less than 1, overfitting prevention (S Ruder, 2016).
- Learning_rate: The learning rate is the step size considered during training which makes the training process faster (Md Z Alom et al, 2019).

Tuning the hyperparameters

Refer to Appendix A – “4-Fold Cross Validation Hyperparameter Tuning” for tabulated results of hyperparameter configurations. Each hyperparameter configuration with 4 cross validation splits has a map score to indicate the optimum hyperparameter configuration.

"To calculate the mAP for a set of detections, the interpolated average precision is calculated for each class, and a mean is calculated over it. For each class, the Average Precision is calculated using the area under the PR(Precision-Recall) curve for the predictions. (M M Vikram et al, 2018)." In addition to this, there is another value of interest that is calculated and displayed within the YOLO map function, called IoU (Intersection over Union). The IoU is the percentage of area that the predicted bounding box covers the of the ground truth bounding box set during the object annotation step in data preparation. Using the combined map and IoU scores for each hyperparameter configuration, regression analysis correlating the hyperparameter values with the maximum mAP and IoU scores can determine the significantly contributing configurations.

Validating the model without bias

Whilst a 2004 study concluded that there is no unbiased estimator of the variance of K-Fold Cross Validation (KCV) (Y Bengio, Y Grandvalet, 2004), KCV is still one of the most popular resampling as it simple, effective and reliable (D Anguita et al, 2009). KCV achieves a low variance evaluation by its technique which consists of splitting a dataset into k independent subsets. Each subset is used to train a classifier and the remaining one is used to evaluate the generalisation error. By repeating this process, each evaluation subset can be independently scored, the measure of variance between the subsets can be also observed. Based the number and size of the subsets, the classifier performance can be estimated when introduced to new datasets. A 2005 study on cross validation variance concluded “a test set that use 25% of the available data seems to be a reasonable compromise in selecting among the various forms of k-fold cross validation” (M Markatou et al, 2005). From the analysis of results of a separate K-Fold study ‘it is clear that the optimal values of k mainly lie between 3 and 4’ (D Anguita et al, 2012).

Refer again to Appendix A – The map scores obtained from the hyperparameter configuration variants indicated that the default hyperparameter values for Yolo (version 3) are likely to obtain the optimum map scores across all trained object classes.

Chapter 4

Results

Proof of concept evaluation

We evaluate an effective YOLO (version 3) object detection classifier on LandSat Satellite images of gold nugget discovery locations identified in "Doug Stone Outdoor Press – Gold & Relic Sites, Metal Detecting Maps". In addition to pinpointing the location of the gold nugget discoveries, the map also illustrates nearby geological objects of interest such as quartz reefs, land contours (gullys) and areas of historical diggings, typically within those gullys.

Also evaluated are LandSat8 Satellite remote sensing images of the locations of each of the purchased "Gold & Relic Site – Metal Detecting Maps".

Images 1 and 4 below – are scanned extracts of "Doug Stone Outdoor Press – Gold & Relic Sites Metal Detecting Map" of the towns Heathcote and Amherst in Victoria, Australia. The popular useful maps illustrate the pinpoint locations of large gold nugget discoveries and the locations of historical diggings in the area. The maps identify the sites of gold diggings that have taken place within land contours (gullys). The map of Heathcote also confirms the existence of interesting geological objects within the general proximity of gold nugget discovery locations such as quartz reefs and surfacing (land erosion).

Image 2 and 5 below are combinations of 3 sample LandSat Satellite images of gold nugget discovery locations from each town. Complementing the satellite imagery is the custom trained YOLO object detection classifier identifying the existence of geological objects trees, water, quartz and red soil within a set prediction confidence threshold above 0% confidence. The LandSat Satellite natural scene images are able to confirm the existence of the geological objects noted in the "Gold & Relic Sites Metal Detecting Maps" and to further to that, they are able to confirm the size of the geological objects noted in those maps.

Image 3 and 6 below are from LandSat8 Satellite remote sensing image browser overlooking the Victorian towns of Heathcote and Amherst. The remote sensing image sample is the furthest level of image zoom capable with image clarity for LandSat8 Satellite image browser. The images confirm the existence of land contours in the towns and nearby hills, but they are unable to pinpoint the exact location of the gold discovery sites.

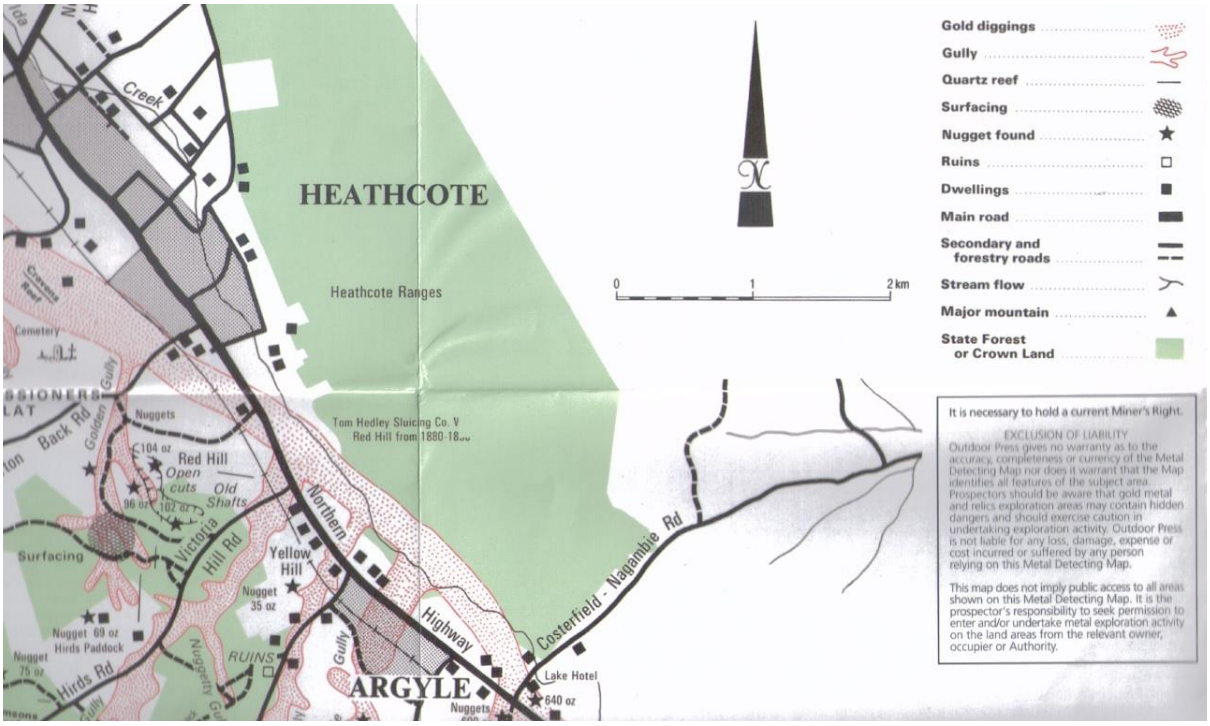


Image 1 – Scanned sample “Doug Stone Outdoor Press – Metal Detecting Map” of Heathcote, Victoria. Protected by copyright, displayed under research (fair use) act of copyright law.

Image 2 – LandSat Satellite natural scene images with YOLO object detection of gold nugget discovery sites in Heathcote, Victoria.

Image 3- LandSat8 Satellite remote sensing image of gold nugget discovery sites in Heathcote, Victoria.

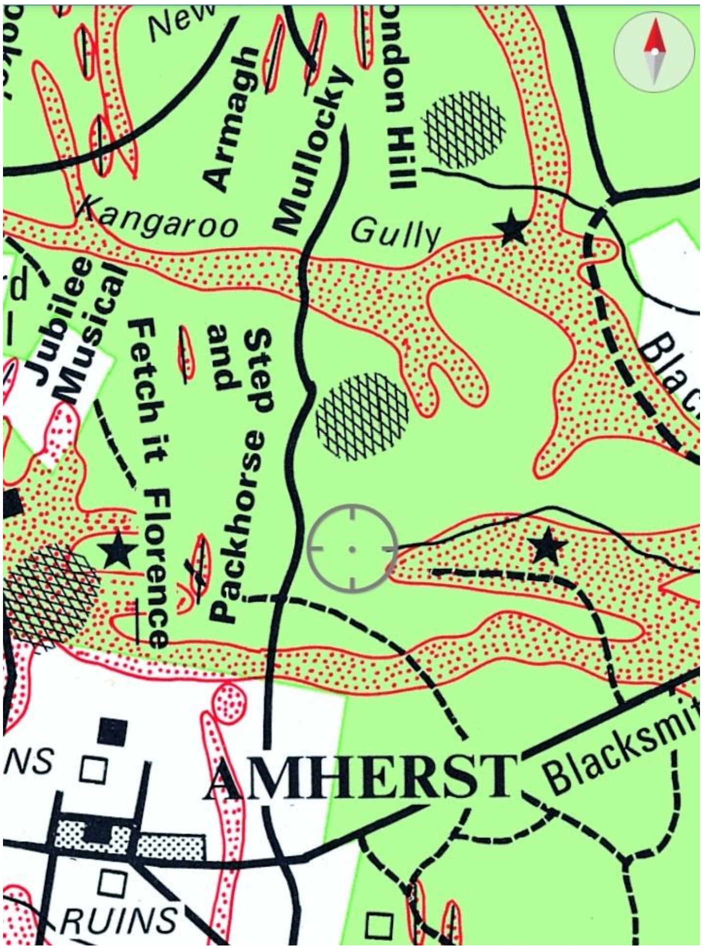


Image 4 - Screenshot sample “Doug Stone Outdoor Press – Metal Detecting Map” of Amherst, Victoria. Protected by copyright, displayed under research (fair use) act of copyright law.

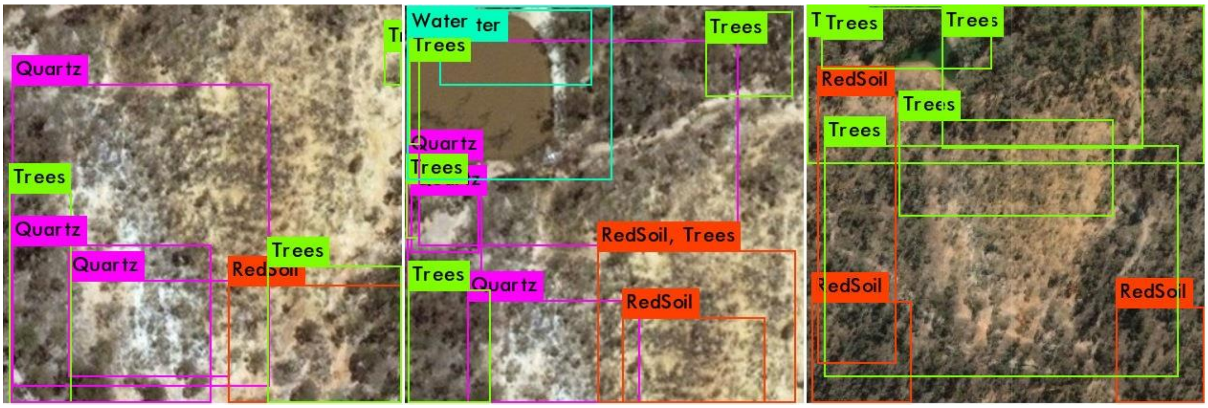


Image 5 – LandSat Satellite natural scene images with YOLO object detection of gold nugget discovery sites in Amherst, Victoria.

Image 6- LandSat8 Satellite remote sensing image of gold nugget discovery sites in Amherst, Victoria.

Chapter 5

Discussion

Proof of concept circumscription

Appendix B – 4-Fold validation results indicate a significant difference in mean average precision scores between the groups of object classes for the predictive model to detect. Foreground object classes (trees and water) in satellite images were significantly more likely to have true positive detections than the background object classes (quartz and red soil). A simple explanation for this outcome is that the foreground objects have more clearly defined shapes that can be clearly pinpointed by pixel location in the annotation step of the classifier training. In contrast, the quartz and red soil are more sparsely and sporadically located in a satellite image. Using basic rectangle shapes to annotate was sufficient in the labelling of the tree and water object classes, however a more sophisticated approach for labelling of quartz reefs and soil textures are required in order to improve mean average precision scores for those more fluid like objects.

A suitable technique to address this situation is named 'Landmark annotation'. 'Combining many landmarks together can create outlines of objects, like a connect-the-dots puzzle. These dot outlines can be used to recognize facial features or analyze the motion and posture of people doing sports activities and other actions' (R Potter, 2019). The usage of dots to pinpoint the many small pixelated points where exposed quartz was visible in a satellite image would allow for a more precise object detection in terms of pixel placement. YOLO map scores are degraded by default if an object classifier prediction box compared to the original annotated bounding box, intersection over union (IoU), is out by more than 50%.

Whilst classifier validation results indicated that variations of the default settings were likely to result in lower overall object detection classifier map and IoU scores, geological objects such as quartz reefs and soil colour variants could potentially be more prone to object detection with higher learning rate values.

The recent advent of Yolo version 4, which according to its subsequent research 'Improves YOLOv3's AP and FPS by 10% and 12%, respectively' (A Bochkovskiy, C-Y Wang, H-Y M Liao, 2020), there is value in repeating the process of constructing Yolo geological object classifiers for fine tuning. Experimentation with larger datasets, more geological object classes and more training epochs could also yield more robust object detection classifier results.

The remote sensing LandSat8 Satellite images have a limited range of focus and can merely the confirm if gold discovery sites are nearby large hills or mountains. A recent study of object detection methods including the Yolo algorithm in remote sensing imagery stated 'Substantial efforts have been devoted more recently to presenting various methods for object detection in optical remote sensing images. However, the current survey of datasets and deep learning methods for object detection in optical remote sensing images is not adequate' (K Li et al, 2020).

Chapter 6

Conclusion and future research

Analysis of gold discovery sites with satellite images with deep learning

In this study, a custom YOLO object detection classifier prototype was constructed, validated and successfully used to detect geological objects in the known locations of many gold nugget discovery sites across Victoria. The prototype was constructed with the free usage of Google Collaboratory Graphics Processing Unit (GPU) and memory hardware and evaluation of average precision scores of individual geological object classes suggested that prediction of some geological objects without a common shape could be improved by adopting 'landmark annotation' methodology when defining the object boundaries in the training datasets.

The object detection prototype proved useful in verifying and measuring by comparison the prevalence of geological objects across many gold nugget discovery sites without the need of visiting and surveying the sites in question. The verification of the geological object existence was performed in a consistent manner with a pre-set confidence threshold of the object detection classification predictions. This combination of geological object detection classifier and satellite imagery combined with gold maps can aid prospectors in comparing and prioritising the visits of future prospect sites.

The range of zoom in LandSat8 remote sensing images were not clear enough to attempt to train a classifier to attempt to predict the boundaries of historical gold digging gullys illustrated in "Doug Stone Outdoor Press – Gold & Relic Sites Metal Detecting Maps". They were useful however to confirm the existence of hills and land contours within the general area of the towns where gold nugget discoveries and historical gold diggings had taken place.

Future research can be extended to improving the robustness of object detection training methodology, exploring and learning the visual geological object characteristics of all known gold nugget discovery locations across the globe and better predict the next gold rush.

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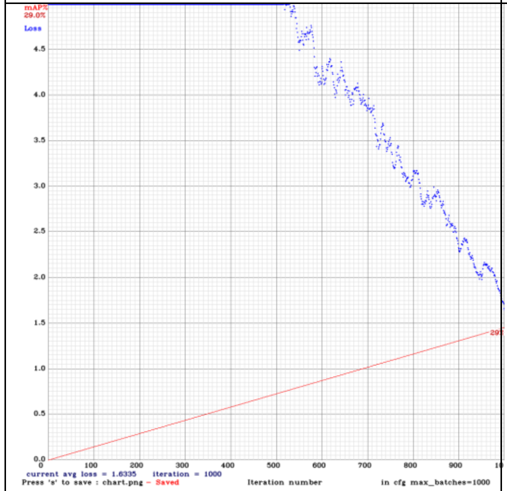
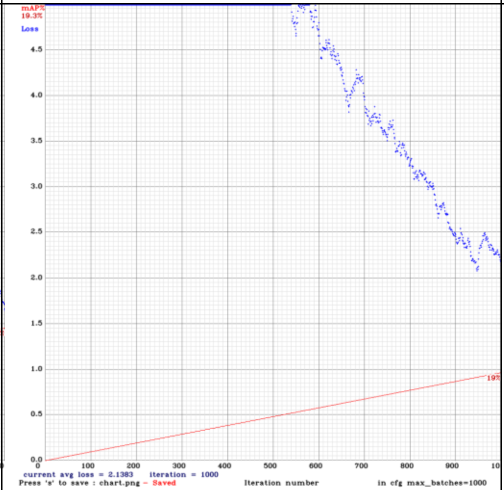
Appendix A – 4-Fold Cross Validation Hyperparameter Tuning

Default learning rate = 0.001, momentum 0.9

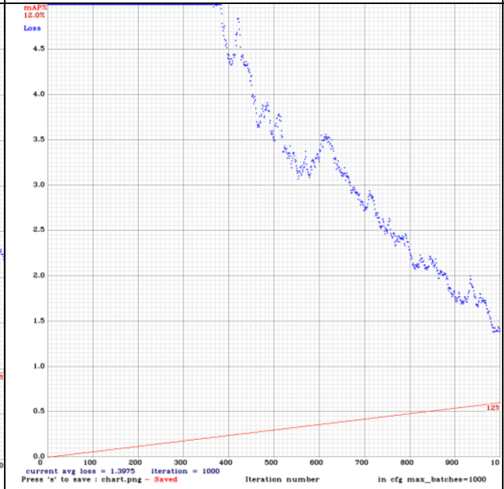
Split 1 – Learning Rate 0.001, Momentum 0.1: map = 29%



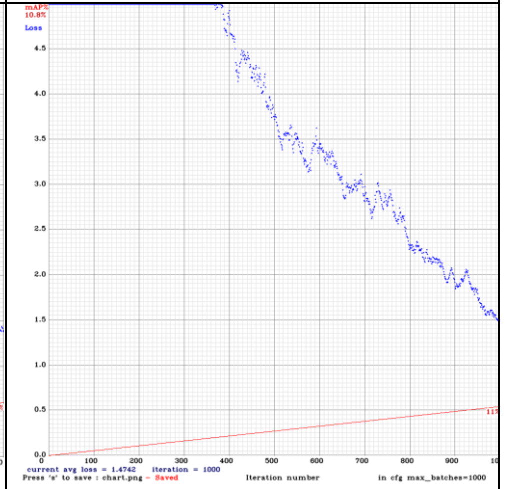
Split 2 – Learning Rate 0.001, Momentum 0.1: map = 19.3%



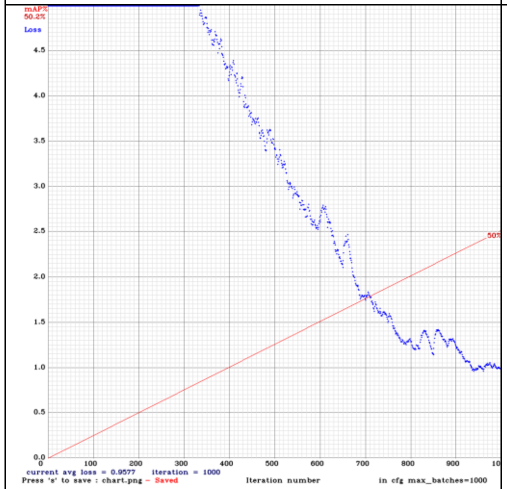
Split 3 – Learning Rate 0.001, Momentum 0.1: map = 12%



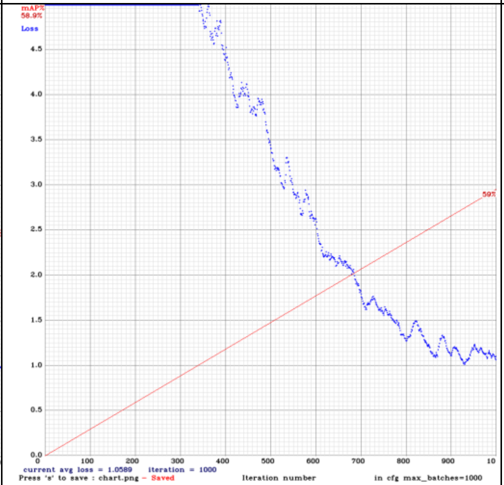
Split 4 – Learning Rate 0.001, Momentum 0.1: map = 10.8%



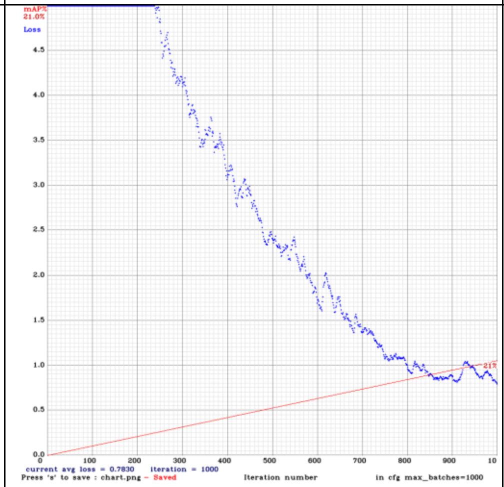
Split 1 – Learning Rate 0.001, Momentum 0.9: map = 50.2%



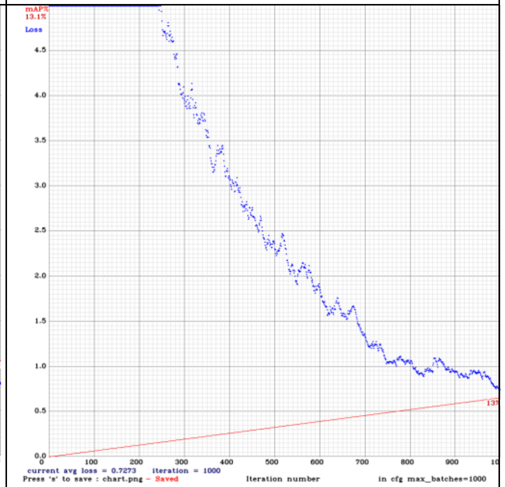
Split 2 – Learning Rate 0.001, Momentum 0.9: map = 58.9%



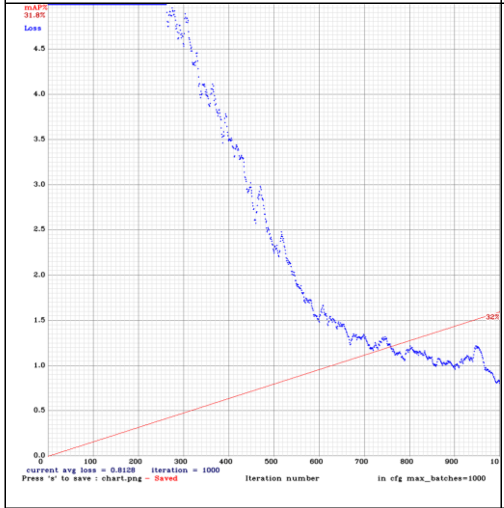
Split 3 – Learning Rate 0.001, Momentum 0.9: map = 21%



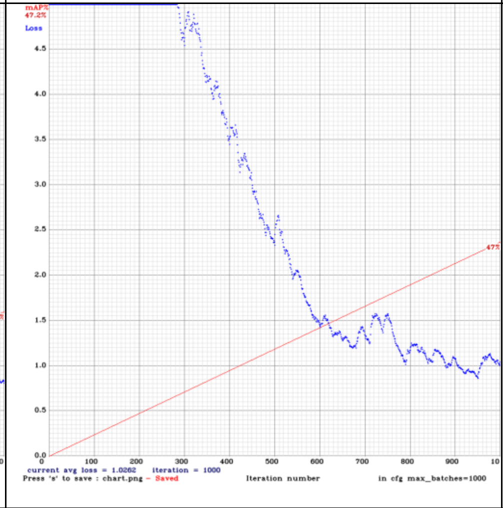
Split 4 – Learning Rate 0.001, Momentum 0.9: map = 13.1%



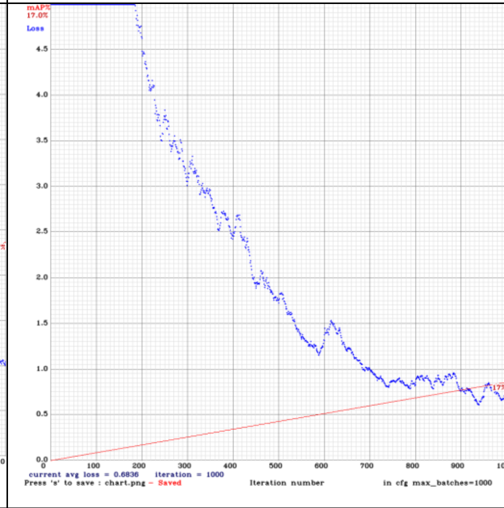
Split 1 – Learning Rate 0.003, Momentum 0.9: map = 31.8%



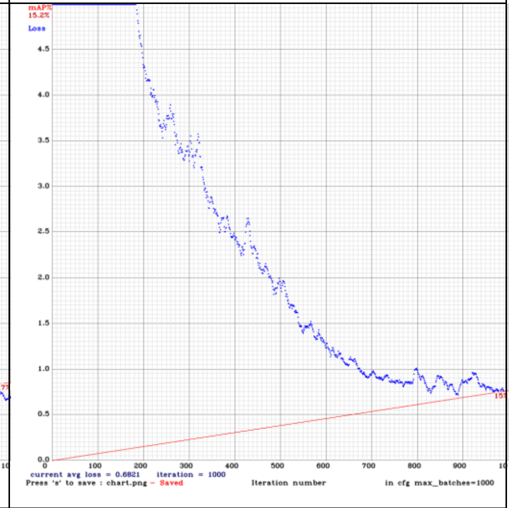
Split 2 – Learning Rate 0.003, Momentum 0.9: map = 47.2%



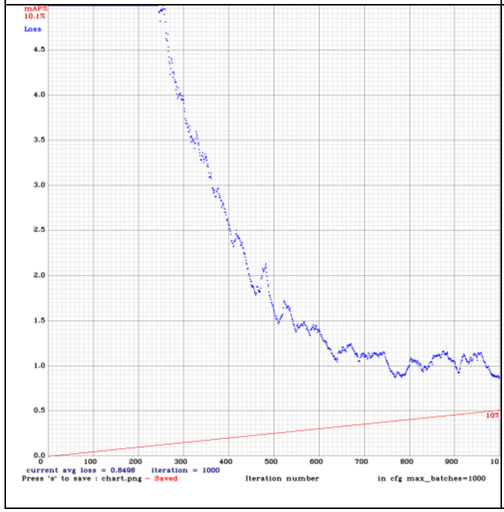
Split 3 – Learning Rate 0.003, Momentum 0.9: map = 17%



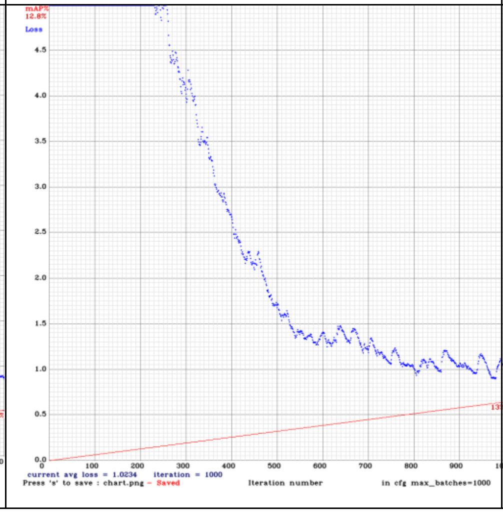
Split 4 – Learning Rate 0.003, Momentum 0.9: map = 15.2%



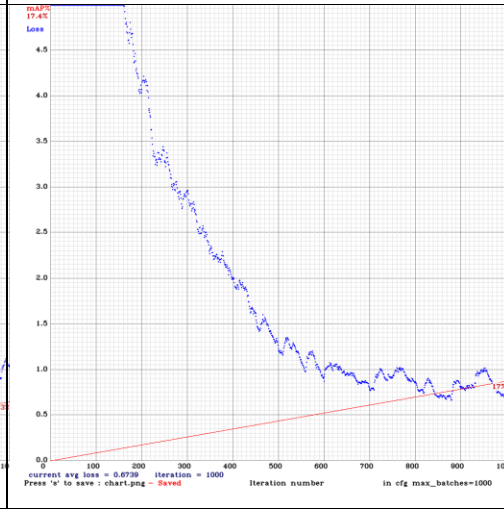
Split 1 – Learning Rate 0.008, Momentum 0.9: map = 10.1%



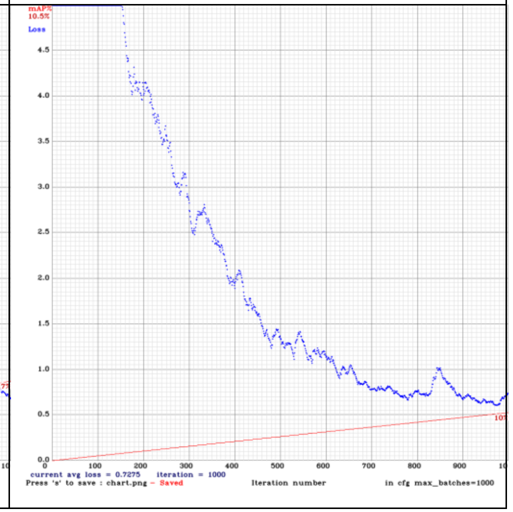
Split 2 – Learning Rate 0.008, Momentum 0.9: map = 12.8%



Split 3 – Learning Rate 0.008, Momentum 0.9: map = 17.4%



Split 4 – Learning Rate 0.008, Momentum 0.9: map = 10.5%



Appendix B – 4-Fold Cross Validation Object Class Average Precision Scores

Learning Rate	Split	Quartz AP	RedSoil AP	Trees AP	Water AP
0.001	1	50	29.53	21.33	100
0.001	2	35	46.89	77.08	76.79
0.001	3	10	6.96	34.29	32.73
0.001	4	1.56	5.71	19.64	25.38
0.003	1	25	12.78	14.57	75
0.003	2	25	59.26	42.78	61.9
0.003	3	0	0.79	23.37	43.94
0.003	4	6.6	2.38	29.88	22.08
0.008	1	0	1.11	1.99	37.5
0.008	2	5.36	8.02	2.78	35.14
0.008	3	9.32	1.71	17.38	41.19
0.008	4	2.04	0	14.19	25.62

ANOVA

Groups	*Count*	*Sum*	*Average*	*Variance*		
Quartz AP	12	169.88	14.15666667	257.8011515		
RedSoil AP	12	175.14	14.595	395.0374091		
Trees AP	12	299.28	24.94	408.2072182		
Water AP	12	577.27	48.10583333	610.0888265		
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	9107.007	3	3035.669141	7.266127172	0.000461582	2.816465817
Within Groups	18382.48	44	417.7836513			
Total	27489.49	47				