Exploring Mediatoil Imagery: A Content-based Approach

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Abstract: Debates over Canada's energy future with its oil sands has become a flashpoint of public interest. Stakeholders have identified advantages, such as economic benefit and global energy demand, and drawbacks, notably environmental and social challenges. This research focuses on discovering how various organizations employ graphics, images and videos in the media, in order to further our understanding of the context and evolution of the oil sands discourse, since the late 1960s. To this end, we created the open-source *Mediatoil* database contains images from six categories of imagery, namely graphics, machines, people, landscape, protest and open-pit. We further created the *Mediatoil-IR* content-based image retrieval system that utilizes SURF descriptors and bags of features. We illustrate how the *Mediatoil-IR* system was used in order to explore and to contrast the imagery used by the various stakeholders, within a multi-class learning setting. Our experimental results show that dividing the images into sub-categories is beneficial for retrieval and classification.

1 INTRODUCTION

The size of digital image repositories continue to expand, with the development of the Internet, reduction in data-storage costs, and improvements in technologies for image-capturing devices (e.g., digital cameras and image scanners, amongst others). To deal with the high volume of pictures, users require dynamic image searching and retrieval tools.

Content-based Information Retrieval (CBIR) systems, which build image descriptors, have had much success when retrieving sets of images that are similar (Liu et al., 2007). In addition, machine learning has long been used in conjunction with image retrieval systems. It has improved the quality of retrieval, both in terms of accuracy and precision, by either grouping images into different categories or classifying a given image based on its unique attributes while predicting its relevant class (Sridhar et al., 2015). Furthermore, CBIR combined with machine learning, have been used in different applications related to query and image analysis (Liu et al., 2007). The application domains of these systems include remote sensing, history, fashion, security, crime prevention, biodiversity information systems, publishing, art collections, retail catalogues, medical information retrieval, face finding, as well as architectural and engineering design.

Despite the many CBIR application areas, one field that is still unexplored is the contested media framing of Canada's oil sands. Our research targets this application area. Specifically, we explore how pictures related to Canada's oil sands, as obtained from various stakeholders, may vary in content. This analysis provides us with new insights into how pictures are used to frame arguments and viewpoints. We are further interested in contrasting different categories of imagery, in order to provide all role-players with an accurate retrieval system. To this end, we developed the ***Mediatoil-IR*** system that combines CBIR techniques and machine learning.

This paper is organized as follows. Section 2 contains a description of the ***Mediatoil*** project. This is followed by Section 3, which introduces the ***Mediatoil-IR*** system. In Section 4, the experimental setup is presented and we discuss the results we obtained. Finally, Section 5 concludes the paper and discusses our future plans.

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2 Mediatoil PROJECT

Campaigns and debates over Canada's energy future with its oil sands have become a flashpoint for political action. Stakeholders driving the discussions may be divided into three broad groups, namely civil society, industry, and government (McCurdy, 2017). By publishing reports, creating still advertisements, and posting videos, oil sands stakeholders seek to influence how the public perceives oil sands development and ultimately the fate of this natural resource (McCurdy, 2017).

Opponents and supporters continue to debate advantages and drawbacks regarding the exploration of the oil sands (Brant, 1962) (Dyer et al., 2017). On the positive side, supporters see the oil sands as a resource that can meet the growing global demand for energy (Dyer et al., 2017). The machinery and other goods required in oil sands production are produced in Central and Eastern Canada, which provides economic benefits to various sectors. Oil sands development also provides economic benefits to Canada by creating jobs and generating taxable revenue. Despite their numerous benefits, the tar sands also pose environmental and social challenges. The synthetic crude derived from bitumen is more carbon-intensive than the one obtained utilizing conventional methods. Moreover, processing bitumen requires using massive amounts of water, which may come from fresh water sources and that can lead to contamination. Land disturbance and use are additional concerns and restoring boreal forests and wetlands to their native state is also a major challenge (Dyer et al., 2017).

Given an assumption that media can be a quite powerful tool for impacting audience opinions on the oil sands development, different visuals used by the various stakeholders need to be explored. Despite numerous application areas of CBIR systems, the domain of oil sands campaigns and their images is still unexplored. While multiple accounts exist, reviewing the tar sand's history reveals that little work has been done on the media debates (McCurdy, 2017). To this end, we are interested in discovering how the struggle over Alberta's oil sands has played out in the reports, publications, and campaigns of different tar sands role-players. We pay particular attention to the graphics and images produced by various organizations, as they are vital resources in any media and thus critical for understanding the context, evolution, and essential characteristics of the oil sands (McCurdy, 2017).

No central repository of tar sands images is available in the literature. To accomplish our objective of analysing oil sands images, we thus designed and implemented the ***Mediatoil*** database, which is publicly available at www.mediatoil.ca. This database contains imagery collected from 99 different stakeholders. We collected reports, photographs, still advertisements, fact-sheets, and videos, spanning a period from 1924 to date. The results reported here concerns images that were collected until October 2016.

Next, we discuss the design of the ***Mediatoil-IR*** system, designed to explore this open source of imagery about the oil sands.

3 Mediatoil-IR SYSTEM

In the ***Mediatoil-IR*** system, the colours associated with our images are represented in the Lab colour space (Tomasi and Manduchi, 1998). There are many reasons for this choice. The gamut of the Lab colour space, that is the subset of colours that may be represented, surpasses the gamut of most other colour spaces. In addition, the Lab space is device independent and constitutes a good approximation of the human visual system especially for lightness perception.

Our image description is based on the Speeded Up Robust Features (SURF) algorithm (Bay et al., 2006), an extension of the Scale-Invariant Feature Transform (SIFT) approach (Lowe, 1999). The SURF method consists of three parts: detection of points of interest, description of their local neighbourhood and matching. SURF uses box filters in order to approximate Gaussian smoothing. An improved computational efficiency is achieved by using integral images, as it required only four additions in order to evaluate the sum of the intensities in a rectangular region of arbitrary size. SURF is a blob or region detection algorithm. The detection of the points of interest is based on the Hessian matrix. The latter is a measure of change in the neighbourhood of a point. The Hessian at point $\left(x, y\right)$ and scale σ is given by

$$H\left(x, y; \sigma\right) = \begin{bmatrix} L_{xx}\left(x, y; \sigma\right) & L_{xy}\left(x, y; \sigma\right) \\ L_{yx}\left(x, y; \sigma\right) & L_{yy}\left(x, y; \sigma\right) \end{bmatrix} \quad (1)$$

where, for instance, the term $L_{xx}\left(x, y; \sigma\right)$ refers to the convolution of the second-order derivative of a Gaussian of standard deviation σ with an image I at point $\left(x, y\right)$.

As mentioned earlier, the Gaussian derivatives are approximated with box filters. In order to obtain scale invariance, the Hessian is evaluated at various scales corresponding to octaves of the smallest scale. These in turn correspond to 9×9, 15×15, 21×21, 27×27, $\ldots$ box filters. The interest points are associated to the maxima of the determinant of the Hessian matrix both in space and in scale. Since the scale varies considerably in between octaves, the maxima of the Hessian matrix are interpolated with a quadratic interpolation technique.

In order to achieve rotation invariance, the Haar wavelet (Chen and Hsiao, 1997) coefficients are evaluated for each point of interest, both in the horizontal and vertical direction, within a neighbourhood spanning six times the scale of interest. The Haar wavelet coefficients are weighted by a Gaussian distribution. The orientation vector of the neighbourhood is evaluated from the horizontal-vertical Haar coefficients graph. Then, a square region, centered on the point of interest and oriented according to the orientation vector, is extracted. This region is rotation invariant.

The rotation invariant region is further divided into 4×4 sub-regions for which the Haar wavelets coefficients are evaluated. These coefficients are weighted by a Gaussian in order to improve the robustness against noise and deformations. The set of all weighted Haar coefficients for every point of interest constitute the image descriptor. The number of points of interest is typically 2000 to 4000 and the number of Haar coefficients, for a given point of interest, is 64. The set of all Haar coefficients associated with a particular point of interest is called a feature. We do not use the SURF descriptors directly. Rather, we construct a bag of visual words (Zhang et al., 2010). These words are obtained by clustering all the Haar *features* with the *k*-means algorithm (Likas et al., 2003). The words correspond to the centres of the clusters. The set of all visual words constitute a dictionary. In order to express a particular SURF descriptor in terms of the dictionary, the closest (in term of Euclidean distance) word associated to each Haar feature is determined. Subsequently, a histogram representing the distribution (frequency of occurrence) of the words associated with the descriptor is created. These histograms constitute the bag of word descriptors which are used for classification and retrieval.

Given an unknown histogram, the corresponding unknown class is determined by using a classification algorithm. A number of classifiers were first trained with the training set and then evaluated with the test set. Once the class of an unknown histogram has been determined by a particular classifier, the most similar N results are retrieved. This is achieved by calculating the Euclidean distance in between the query histogram for which the class has been determined and all known histograms belonging to the same class. The first N best results are then displayed to the user.

Figure 1 shows an example where N was set to twenty and where the query image comes from the protest category. In this case, our algorithm correctly predicted the class and subsequently retrieved the nearest twenty images, all belonging to the Protest category.

4 EXPERIMENTATION

The ***Mediatoil*** website was developed in Visual Studio 2015 with C#, Razor, and Bootstrap frameworks for the front-end, with SQL Server 2014 as a back-end. Creating a website was necessary not

(a) Query Image

(b) First 20 images retrieved

Figure 1: Illustration of ***Mediatoil-IR*** system against the Protest category.

only to support our study but also to make our information available to researchers investigating bituminous sands. The classification experiments were conducted using Matlab 2016 on a 64-bit architecture running Windows 7 with 16 GB of memory. Note that the six categories of images namely graphics, machines, people, landscape, protest and open-pit were initially labelled by a domain expert. These categories where determined by experts in media studies. The search process returns the indexes for all of the pictures that match the query image's visual words, ranked from best (nearest) to worst. The maximum number of retrieved images was set to 20, as determined after consultation with our domain experts.

4.1 Exploring Stakeholder Imagery

The Stakeholders in the ***Mediatoil*** database may be divided into six categories, namely Aboriginal Peoples, Civil Society: Pro-Oil Sands, Civil Society: Anti-Oil Sands, Industry, Provincial Government, and Federal Government. (Note that the Aboriginal Peoples category contained only 15 documents, and our analysis suggests that all of the images from this category were against the oil sands. Consequently, our discussion will be focused on the other five categories.)

The pictures from the Industry and Provincial Government categories may be dated back to 1967 and 1925, respectively. The year 2004 was a breakthrough year when Civil Society images related to the oil sands came into existence, but they produced only two documents for the period 2004-2005. It was thus found that 2006 was a distinguishing year, given that this is when Civil Society became more politically active in opposing the oil sands.

Figure 2 depicts some imagery used by the three main stakeholders, namely Suncor Energy, the Government of Alberta, and Environmental Defence. Based on the number of documents available, these entities are leaders in Industry, Government, and Civil Society: Anti Oil Sands, respectively.

Figure 3 shows a comparison of the type of images used by the three main organizations, as the debate evolved over time. The evaluation includes pictures from 2006 to mid-2016 (when data collection stopped). From the graphs, it was clear that Suncor Energy was the only organization actively giving its views on the tar sands in the years from 2006 to 2008. In 2008, the Government of Alberta focused on the controversial tar sands by utilizing machine/infrastructure pictures as the instrument for promoting its views. Suncor Energy proceeded in the same way, although in addition to machines they also promoted their thoughts using the open-pit and people classes.

In contrast, as Environmental Defence was in its inception phase, they had only three documents in that year. This small amount of images was due to the fact that this organization was newly formed. The figures show that the imagery focusing on people and graphics dominate the imagery used by Suncor Energy. Interestingly, there was a later tendency to move towards graphics rather than people, while Environment Defence tends to increase their focus on graphics, protest and people.

The focus on machines is steadily declining, as the debate continues. Further, Suncor Energy has less focus on open-pit, while the other role-players do engage this argument later in the timeline. The two main themes commonly found in the Government of Alberta images were people (workers, eminent personalities in formal apparel) and oil sands infrastructure. The earliest recorded picture was from mid-1920s. After 2006, the use of people in photographs was reduced by 25%, while the use of machines in images was reduced to one third in comparison to the earlier period. However, landscape imagery showed an increase by a factor of two during the same period.

Government and industries were facing rising opposition from civil society about the destruction of natural resources. Consequently, landscape images were used by government to show how well the oil companies are doing vis-à-vis returning the land to its natural state.

In addition, there was a decline in using the images of well-known pro-oil sands advocates as well as activists, by all role players. Rather, the imagery focused on generic images of families and nature.

As expected, industry and government groups in favour of the oil sands produced documents that show the positive impact on life, society and culture. Their focus was on showing oil as an essential commodity in every aspect of our existence, while the civil society opponents focused more on graphics containing protest imagery and pictures of actual protesters.

4.2 Multi-domain Learning

In this section, we discuss the results when exploring the data in a supervised learning setting. Recall that our database contains six classes of images, as

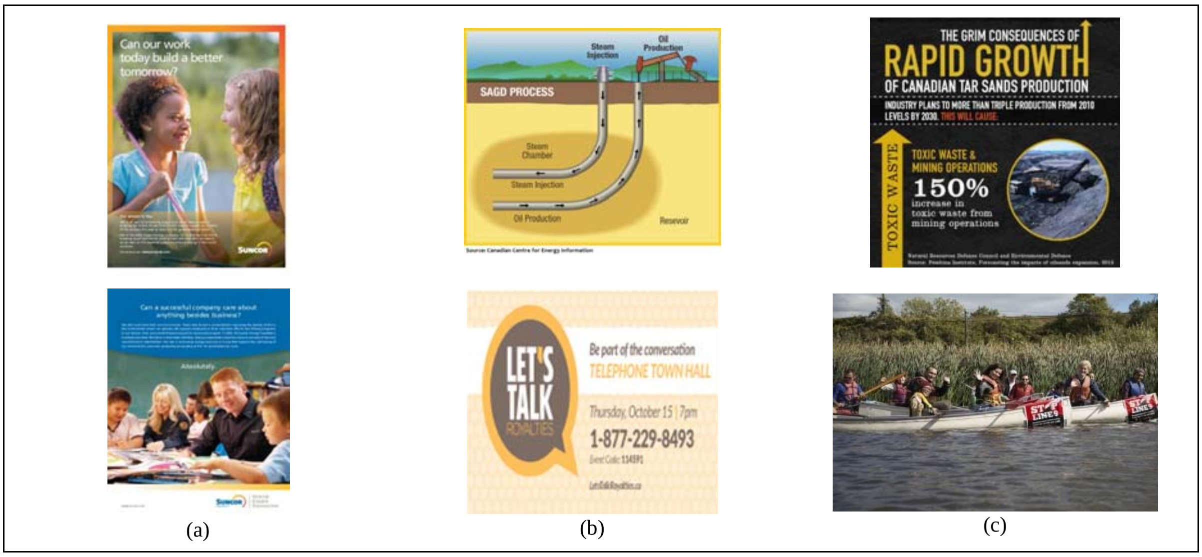

Figure 2: Contrasting imagery used by (a) Suncor Energy, (b) Government of Alberta and (c) Environmental Defence.

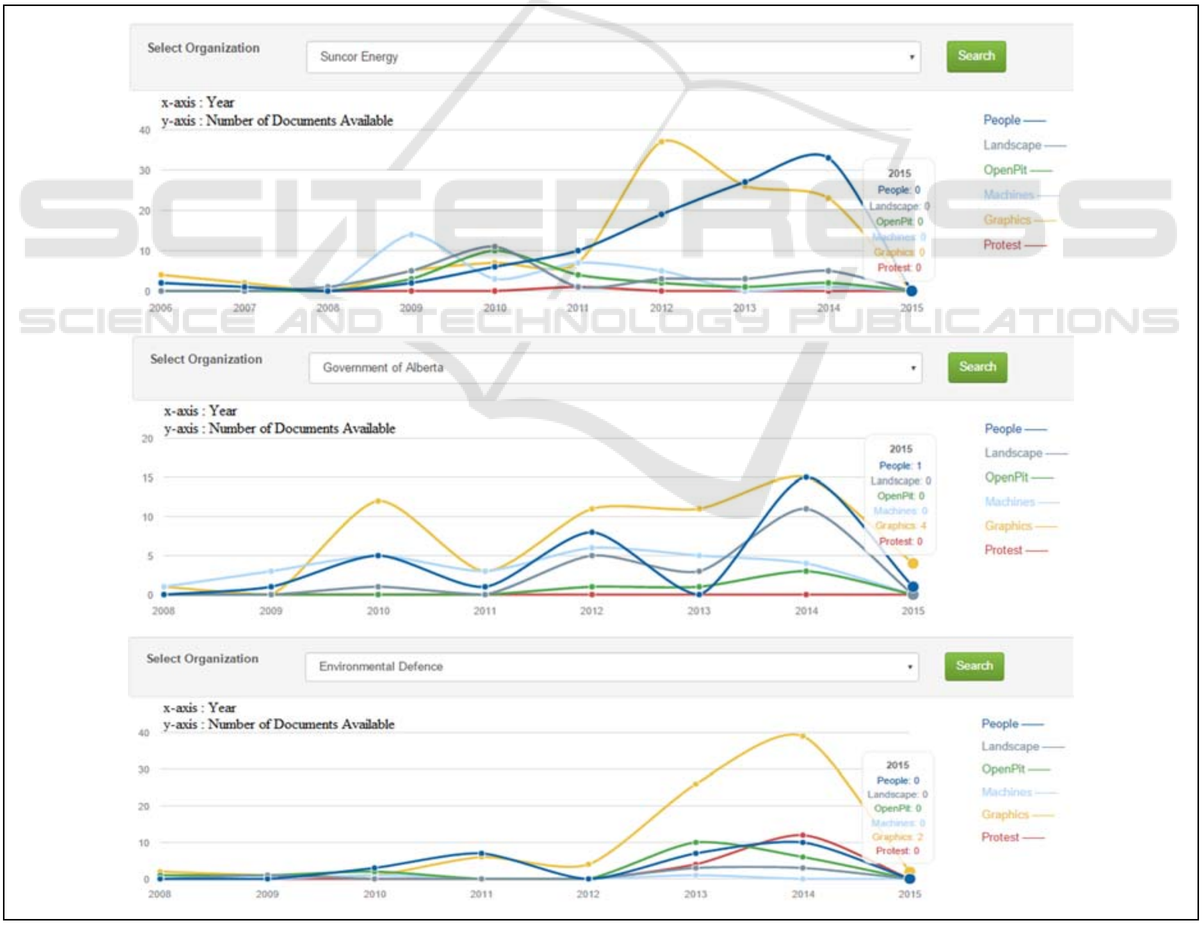

Figure 3: A comparison of the timelines of the imagery used by the three main players in the oil sands debate.

labelled by a domain expert. Table 1 summarizes the membership of the six classes.

Table 1: Number of images in each category.

Category	Membership
People	533 (30.3%)
Protest	109 (6.0%)
Machines	216 (12.3%)
Open-pit	142 (8.1%)
Landscape	192 (10.9%)
Graphics	569 (32.3%)
Total	**1760 (100%)**

Throughout this study, we followed a ten-fold cross-validation approach and report the averaged results of ten runs. Initially, we trained a number of classification algorithms in this six-class learning setting. We conducted four different sets of experiments. Our preliminary experimental evaluations confirmed that the quadratic support vector machine (SVM) method performed best, in terms of overall accuracy (Amari and Wu, 1999). (Note that we used statistical significance analysis through the Friedman and adhoc Nemenyi tests for this task (Japkowicz and Shah, 2011).)

Table 2: True class versus predicted class (count).

Grphcs	**463**	12		1	85	5
Indstr	37	**81**	28	16	86	1
Lndscp	37	28	**67**	12	50	2
OpnPt	23	19	16	**57**	27	
Ppl	65	46	18	7	**356**	5
Prtst	8	15	6		72	**8**
	Grphcs	Indstr	Ldscp	Opnpt	Ppl	Prtst

Next, we explored the results in order to obtain insights into the nature of misclassifications. To this end, tables 2 and 3 depict the results of the quadratic SVM classifier in terms of a confusion matrix, as well as the true positive versus false negative rates. The tables show that the classifier was most successful when classifying the graphics and people images. The tables further indicate that, as expected, that the people and protest categories were the most similar, as they both contained humans. In this case, 66% of the protest images were misclassified as people, due to the categories' similar characteristics. A protest image typically contains people together with some posters, and this led to the protesters being grouped into the more people category. That is, the classifier discarded the poster information and rather focused on the humans present.

Table 3: Class precisions in terms of percentages.

Grphcs	**82%**	2%		<1%	15%	1%
Indstr	15%	**33%**	11%	6%	35%	<1%
Lndscp	19%	14%	**34%**	6%	26%	1%
OpnPt	16%	13%	11%	**40%**	19%	
Ppl	13%	9%	4%	1%	**72%**	1%
Prtst	7%	14%	6%		**66%**	7%
	Grphcs	*Indstr*	*Ldscp*	*Opnpt*	*Ppl*	*Prtst*

The graphics category resulted in fewer misclassifications. Given that graphics contained computer-assisted visuals (including text), whereas categories such as landscape and open-pit mostly included outdoor photographs, the ***Mediatoil***-IR system was able to detect these differences. A similar observation holds for protest and open-pit images. As the characteristics of these two classes were quite distinct, not a single instance of open-pit was misclassified as belonging to protest. The results for the images that are often of mixed content, namely landscapes and open-pit, confirms that it is challenging to distinguish in such a context.

Our ***Mediatoil*** database contains a wide range of distinctive images. We therefore concluded that exploring the subsets of images separately, could potentially yield better results. Based on this observation, we proceeded to train the classifiers in an incremental manner.

We next describe the results of this three step learning process. In the first domain, we considered our entire dataset and converted it into a binary classification problem. That is, we combined the generic people grouping with the protest category (both which includes humans in the images) into one class, and contrasted these images against the remaining four categories ("non-people"). In the second and third domains, we proceeded to split the original datasets in two. For domain two, we turned our attention to the generic people category and opposed it to the protest category. This is a challenging learning task, since (as noted above) most protest images include some humans, often together with graphical elements such as posters. Our aim here was to determine whether we could achieve a higher recall than the original disappointing number of 7%. The third set of experiments only considered the four "non-people" classes, namely machines, open-pit, landscape and graphics. Again, it follows that an open-pit image may contain machines and also be part of a landscape. Table 4 summarizes the details of these domains, in terms of class memberships.

Table 4: Summary of three learning tasks.

Task	Classes	Membership
1	People + Protesters	642 (36%)
	Non-People	1118 (64%)
2	People	533 (83%)
	Protest	109 (17%)
3	Machines	216 (19%)
	Open-pit	142 (13%)
	Landscape	192 (17%)
	Graphics	568 (51%)

The reader will notice that all of these datasets are imbalanced, notably domain 2, where the skew ratio is high (He and Garcia, 2009) (Agarwal et al., 2015) . Note that, in most imbalanced domains, the minority class is often deemed to be of higher important. This is not the case in our research, since we are interested in classifying all the classes accurately.

Table 5: Recall for individual classes in three domains.

Class	L-SVM	Q-SVM	Boosting
People	67%	**72%**	57%
Non-People	**92%**	91%	83%
People	**99%**	**99%**	83%
Protest	14%	24%	**61%**
Machines	**59%**	**59%**	49%
Open-pit	**51%**	49%	48%
Landscape	45%	47%	**79%**
Graphics	**96%**	95%	95%

We report the results for three difference classification techniques, while using the one-versus-one (OVO) approach for multi-class learning (Gatar et al., 2011) (Tomar and Agarwal, 2015). Firstly, we employed a linear SVM, where the kernel used was linear with degree equal to one. The second technique is a quadratic SVM, as introduced above (Amari and Wu, 1999). The third method is the RUSBoost boosting ensemble, with 30 classification and regression trees (CART) decision trees as base learners. This boosting algorithm utilizes a hybrid data sampling approach and has been shown to be highly suitable for imbalanced domains (Seiffert et al., 2010).

Table 6: Accuracies for the classifiers in three domains.

Domain	L-SVM	Q-SVM	Boosting
P vs nP	82.67%	**83.12%**	73.80%
P vs Pt	85.04%	**86.13%**	77.88%
M, L, O, G	**74.41%**	74.23%	60.82%

Tables 5 to 7 summarize our results, measured in terms of recall, precision and accuracy. Table 6 shows that the support vector machines had the highest overall accuracies in these three domains. Our results indicate, as expected, that the classifiers are consistently biased towards the majority classes. These accuracies further suggest that linear SVM, quadratic SVM, and RUSBoost had some limited success in identifying the minority classes. The results also indicate that linear and quadratic SVM do not degrade the performance against the majority class, in contrast to the RUSBoost technique, where the majority class accuracies for domains 1 and 2 are lower.

Next, we consider the recall and the precision values. Table 5 shows that, in domain 1, we found that quadratic SVM achieves the highest recall (72%) for the minority class, followed by linear SVM (67%). In domain 2, RUSBoost secured a recall of 61% for the protest category. However, this gain results in a loss of recall for the majority class (people). Domain 3 (machines vs. open-pit vs. landscape vs. graphics) has three minority classes, namely machines, open-pit, and landscape and all three algorithms favour the majority class.

Table 7: Precision for individual classes in three domains.

Class	L-SVM	Q-SVM	Boosting
People	**82%**	**82%**	66%
Non-Ppl	83%	**84%**	77%
People	85%	86%	**91%**
Protest	**93%**	81%	40%
Machines	**65%**	64%	48%
Open-pit	67%	**70%**	43%
Landscape	63%	**69%**	39%
Graphics	79%	79%	**84%**

Table 7 shows that, in four cases, the quadratic SVM algorithm provided the highest scores in terms of precision. In five of the categories, at least one of the classification algorithms yield precision rates higher than 80%. The precision rates for the minority classes in domain 3, namely machines, open-pit and landscape were 65% or higher. The three algorithms produce comparable results, i.e. precision rates are in the same ranges.

4.3 Lessons Learned

The application of content-based information retrieval and knowledge discovery in a real-world domain is always a challenge. In our case, the main issues faced were the following.

According to communications researchers, who were our domain experts, the images belonged to distinct and easily distinguishable categories.

However, from a content-based retrieval point of view, these images contained very similar features. This fact was most notable in the images that contain human subjects. For example, industry images almost always contain some engineers and other industry workers, often depicted as wearing protective helmet. It follows that the protest category are also problematic, since it is not always evident to distinguish protesters from the generic people category. Further, many landscape images could contain images of hikers, swimmers, anglers or canoers. This posed a challenge for accurate classification and retrieval.

One aim of our research was to explore whether using only content-based descriptors, without any metadata, would suffice in terms of precision and accuracy. Our results show that we obtained high results for the categories that are clearly distinct. The process of subdividing the images into subcategories led to higher recall, precision and accuracies and was beneficial to all the classification algorithms.

It follows that we could also make use of meta-data such as tags and keywords, in order to possibly augment the content-based descriptor. Manual image annotation is time-consuming, laborious and expensive; to address this, we are currently investigating the use of automatic tagging systems and/or crowd-sourcing (Datta et al., 2007). The use of crowd-sourcing may be problematic, since the annotators may potentially be biased towards a specific cause.

The experimental results further show that no single classifier dominated and suggests that a multi-strategy learning method, which employs some form of meta-learning, may be beneficial. For instance, the meta-learner would select the current classifier with the highest precision, and suggest these results to the user.

A further problem was the fact that the data were unbalanced. This aspect needs further attention, since the classifier explicitly designed for handling class imbalance did not outperform. Rather, this classifier sacrificed the majority class accuracies, in order to improve on minority class predictions. As ***Mediatoil*** is an ongoing project and one of our aims is to obtain additional images from these minority classes. We are also planning in utilize additional techniques to address the multi-class imbalance issue (Agarwal et al., 2015).

Recall that the original class labels were assigned by domain experts, through visual inspection. Originally, each image was grouped into only one class. The domain experts inspected our classification results and it was conceded that some of these classes are subject to interpretation. Further assessment by our domain experts confirmed, after the fact, that it may be possible for an image to fall in more than one class. We aim to explore this aspect in our future work.

5 CONCLUSIONS

In this paper, we introduced the ***Mediatoil-IR*** system, designed in order to explore an evolving repository of imagery regarding the Canadian oil sands. We explored the images using content-based retrieval combined with supervised machine learning. Our goal was to illustrate how information retrieval and knowledge discovery may be used in order to map the contrasting viewpoints of different stakeholders in this debate. Further, our system was designed to investigate the different use of categories of images during the lifetime of the ongoing debates. Our analysis shows that the imagery used by various stakeholders differed considerably, and changed over time. Our results further indicate that dividing the images into sub-categories is beneficial for retrieval and classification.

It follows that our future research will focus on handling skewed domains where the class imbalance is high, in order to ensure that the retrieval of minority class images is precise. The use of key-words or tags, together with the content-based indexing, is another avenue that we wish to further explore. We also plan to further explore the video and text content, as contained in the ***Mediatoil*** repository.

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