Milestone #3

Within this paper, we will discover the importance Image Classification Models have within the data science community and the innovations Image Classification Models are able to offer. Our group will examine various security issues and related concerns that are connected to the relatively new field of Image Classification Models. Typical of up and coming technological developments, along with the many benefits that are already being experienced through the use of Image Classification techniques, many people have begun to uncover some of the unethical uses of these technologies. Our efforts will describe the various pros and cons connected to the development of this innovative process. The team's overall goal for this paper is to showcase the importance of Image Classification Models within the data science field.

Introduction

Image classification has played an important role in everyday uses and the growth of data science. According to the case study featured on Science Direct, Image Classification refers to the process of computer vision being able to classify an image to its visual content. The use of algorithms to classify is used in everyday life from experimentation to visual tagging on social media. The algorithms used for image classification are able to be seen as both positive and negative within the data science community.

Our paper is presented to the reader as follows; the first section will showcase image classification models used within multiple industry fields and how it can benefit society. The second section will feature the unethical aspects of image classification. Our final section will summarize what we discovered and discuss why our group believes this is the importance to the data science community

Sources to cite in these sections for ACM
https://www.sciencedirect.com/topics/computer-science/image-classification

Kaeli, David R. *Heterogeneous Computing with OpenCL 2.0*. Morgan Kaufmann, 2015.

Utilization of Image Classification within Multiple Fields

Image Classification can be suitable for many fields of work around the world. Below we will feature many experiments where image classification was utilized to determine outcomes.

Sound Source Distance Estimation with Image Classification

Yiwere and Rhee established a study that presented the use of convolutional recurrent neural networks of sound source distance estimation. The study used featured an image classification model where they wanted to classify audio signals to predefined distances of one - three meters by the orientation angle. To create the classification variables to discover these distances, the audio signals needed to be reinvented into spectrograms to present the visual aspects needed to train the convolutional recurrent neural network.

Studies such as this could help police force industries to determine the length of shots fired within a critical moment during their work lives. Possibly, this type of innovation could be implemented into their body cameras microphone and create a spectrogram of the audio to determine the distance of gunfire. It is possible to determine specific types of gunfire via a simple Github experiment performed by tusharsignh62 using spectrograms and image classification. Our team believes there is a possibility for this in the near future.

Burned Area Mapping

One of the fields in which image classification technologies have been developed is within mapping of burned landscapes such as forest fires. The idea is one of quantifying the effects of fires on landscapes. Developers of these technologies have worked to figure out how to select and prioritize treatments that should be applied once a fire has occurred (8). One of the major goals has been that of planning and monitoring restoration activities.

The images are intended to provide baseline information for future monitoring efforts. Satellite remote sensing is used for gathering post-fire related information in a cost effective and timely manner. An increase in extreme fire events has been recorded in recent years and has increased the perceived need to accurately map burned areas accurately. Researchers have concluded that the combination of object features, such as spectral values, together with contextual information, have made it possible to avoid confusion in the classification between burned areas and other land cover types.

Automatic Ship Classification

Automatic ship classification from aerial images has been studied for many years, but recently this technology has shown remarkable improvements (7). Methods have been developed for determining if an aerial image of visible spectrum contains a ship or not. This determination is important for officials who must perform maritime surveillance. Their activities center around the detection of activities such as: smuggling, control of air pollution, spills, or oil slicks. A wide variety of sensors are used for these tasks including the Automated Identification System, the Vessel Monitoring System, and the Synthetic Aperture Radar.

Deep learning is used with the Convolutional Neural Networks (CNN) in which the networks can be trained with a backpropagation algorithm. The network architectures and deep learning techniques focus on remote sensing data in which features are extracted from aerial imagery. These architectures are used for object detection and scene classification of remote sensing images within various categories.

Automated Classification of Genre within Scientific Research Findings

Scientific information is being generated at an exponential rate, and a huge challenge is that of being able to properly classify scientific research findings through automated procedures. Storage of scientific information takes place among a wide variety of media including: scientific papers, raw data, laboratory notes, emails, and letters. Mainly it is through an analysis of metadata that data of all these varied types is able to be identified and classified. It is very expensive to manually acquire this metadata; therefore researchers have been working on automation models to be able to extract metadata within specific domains or genres (11).

Along with other classifier techniques, such as a language model classifier, a semantic classifier, and a contextual classifier, the image classifier looks at various pages of a scientific document after they have been rendered as images. The image classifier uses the module pdftoppm from XPDF to extract the pages as images. The resulting image is divided into a grid. Python’s image library is then used to extract pixel values in each region of a page. The result is that the image classifier technique enables the overall classifier system to determine the type of scientific genre a particular scientific document should fit into.

Sources to cite in this section for ACM
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6982911/
https://github.com/tusharsingh62/Gunshot-sound-classification-using-deep-learning

tusharsingh62. “tusharsingh62/Gunshot-Sound-Classification-Using-Deep-Learning.” *GitHub*, github.com/tusharsingh62/Gunshot-sound-classification-using-deep-learning.

Unethical Applications of Image Classification models.

The possibilities of image classification are seemingly endless. Unfortunately, this does not mean that all applications are exclusively ethical. In recent media and trending technology there are some examples of unethical uses of image classification technologies. Although the examples share both ethical and unethical applications it shows examples of how unethical use can have detrimental and lasting effects. The listed examples are and have been used recently and will continue to grow with technology.

The first unethical example of image classification is that of style transfer. This example is arguably unethical but does allow for unauthentic artistic expression. Style transfer or neural style transfer is the task of learning style from one or more images and applying that style to a new image [3]. One example of this is taking the style of famous painters and applying this to any other image. This seems somewhat harmless, but does this diminish artistic expression? Most know this as applying a filter to an image. Even though image filtering appears harmless there are some lesser known and more unethical cases. An example of unethical filtering is that of social media which is used by many young and impressionable adolescents. It is not the fact that adolescents utilize filters but rather that these images may be perceived as reality. The use of filtering allows for image modification that can make one appear more enhanced than reality causing impressionable people to think that is achievable when it is likely not.

A widely known example of image classification technology is that of facial swapping in not only images but also video applications. With advancements in technology these applications have become readily available. Most often these applications are used in an ethical manner but sometimes they are not and this can lead to misinformation or unauthentic behaviors. Most have seen this through video examples on social media. This recent spike in inauthentic behavior is often known as deep fakes. A deep fake can be defined as applying one person's face over another's utilizing artificial intelligence. Digital images should be acquired in a manner that does not intend to deceive the viewer or to obscure important information that might allow for alternative interpretations of the data [4]. Although comical in most examples, this does allow for serious consequences if the video is convincing enough. One could imagine the consequences of convincing deep fakes on political or celebrity figures. There is a possibility to unjustly harm another's career or livelihood.

Conclusion

Image Classification has the potential to be one of the most impactful and influential data science tools. Image Classification has made great progress in a variety of areas. From computer aided diagnosis schemes used in the automatic detection of cancer cells in relation to benign diagnosis, to producing a land and global map through remote sensory. The use of multiple remote-sensing features, including spectral, spatial, multitemporal, and multisensor information aids emergency responders with locating fires, location of survivors in natural disasters, and civil engineering to address global development challenges with roads and load bearing bridges. Accuracy in image assessment is a vital factor in Image Classification success as well as the appropriate classification procedure.

ACM Citations

Ahmad, J. Muhammad, K. Lee, M. Baik, S. (2017). “Endoscopic Image Classification and Retrieval using Clustered Convolutional Features” Journal of Medical Systems, 41(12): 1-12.

Bonner A.. 2019. The Complete Beginner's Guide to Deep Learning: Convolutional Neural Networks. (February 2019). Retrieved December 22, 2019 from https://towardsdatascience.com/wtf-is-image-classification-8e78a8235acb

[3] Brownlee J. 2019. 9 Applications of Deep Learning for Computer Vision. (July 2019). Retrieved February 13, 2020 from https://machinelearningmastery.com/applications-of-deep-learning-for-computer-vision/

[4] Douglas W. Cromey. 2010. Avoiding Twisted Pixels: Ethical Guidelines for the Appropriate Use and Manipulation of Scientific Digital Images. *Science and Engineering Ethics* 16, 4 (2010), 639–667. DOI:http://dx.doi.org/10.1007/s11948-010-9201-y

G. Cavallaro, M. Riedel, M. Richerzhagen, J. i Benediktsson, and A. Plaza. 2015. On Understanding Big Data Impacts in Remotely Sensed Image Classification Using Support Vector Machine Methods. *IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING* 8, 10 (October 2015), 4634–4646.

Brian L. DeCost and Elizabeth A. Holm. 2015. A computer vision approach for automated analysis and classification of microstructural image data. (August 2015). Retrieved December 22, 2019 from https://www.sciencedirect.com/science/article/pii/S0927025615005066

Gallego, A. Pertusa, A. Gil, P. (2018). "Automatic Ship Classification from Optical Aerial Images with Convolutional Neural Networks" Remote Sensing. Vol. 10 Issue 4, p511.

Ioannis Z. Gitas, George H. Mitri, and Gemma Ventura. 2004. Object-based image classification for burned area mapping of Creus Cape, Spain, using NOAA-AVHRR imagery. *Remote Sensing of Environment* 92, 3 (June 2004), 409–413. DOI:http://dx.doi.org/10.1016/j.rse.2004.06.006

Wei Hu, Yangyu Huang, Li Wei, Fan Zhang, and Hengchao Li. 2015. Deep Convolutional Neural Networks for Hyperspectral Image Classification. (July 2015). Retrieved December 22, 2019 from https://www.hindawi.com/journals/js/2015/258619/

Yunhyong Kim and Seamus Ross. 2007. Detecting Family Resemblance: Automated Genre Classification. *Data Science Journal* 6 (March 2007). DOI:http://dx.doi.org/10.2481/dsj.6.s172

D. Lu and Q. Weng. 2007. A survey of image classification methods and techniques for improving classification performance. (March 2007). Retrieved December 22, 2019 from https://www.tandfonline.com/doi/full/10.1080/01431160600746456

Waseem Rawat and Zenghui Wang. 2017. Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review. *Neural Computation* 29, 9 (August 2017), 2352–2449. DOI:http://dx.doi.org/10.1162/neco_a_00990

Adrian Rosebrock. 2017. Image classification with Keras and deep learning. (February 2017). Retrieved December 22, 2019 from https://www.pyimagesearch.com/2017/12/11/image-classification-with-keras-and-deep-learning/

Changjing Shang and Qiang Shen. 2002. Rough Feature Selection For Neural Network Based Image Classification. *International Journal of Image and Graphics* 02, 04 (March 2002), 541–555. DOI:http://dx.doi.org/10.1142/s0219467802000792

Jacob, N. Sowmya, V. Soman, K.P. Thampi, Sabu M. El-Alfy, E.. (2019). “Effect of denoising on hyperspectral image classification using deep networks and kernel methods” Journal of Intelligent & Fuzzy Systems, Vol. 36 Issue 3, p2067-2073.

K. Wang, D. Zhang, Y. Li, R. Zhang, and L. Lin. 2017. Cost-Effective Active Learning for Deep Image Classification. (January 2017). Retrieved December 22, 2019 from https://arxiv.org/pdf/1701.03551.pdf

Li Y. Xie X. Shen L. Liu S. (2019). “Reverse active learning based atrous DenseNet for pathological image classification” BMC Bioinformatics [BMC Bioinformatics], ISSN: 1471-2105; Vol. 20 (1), pp. 445.

Yiwere M; Rhee EJ, Sensors (2019). “Sound Source Distance Estimation Using Deep Learning: An Image Classification Approach”(Basel, Switzerland) [Sensors (Basel)], ISSN: 1424-8220; Vol. 20 (1).

https://www.sciencedirect.com/topics/computer-science/image-classification

Anon. Retrieved December 22, 2019 from
https://www.spiedigitallibrary.org/conference-proceedings-of-spie?SSO=1

Miao Wu, Chuanbo Yan, Huiqiang Liu, Qian Liu; Automatic classification of ovarian cancer types from cytological images using deep convolutional neural networks. *Biosci Rep* 29 June 2018; 38 (3), Retrieved from: https://doi.org/10.1042/BSR20180289

Arya Pamuncak, Weisi Guo, Ahmed Soliman Khaled and Irwanda Laory
Published:04 December 2019, Retrieved from: https://doi.org/10.1098/rsos.190227
https://royalsocietypublishing.org/doi/10.1098/rsos.190227

Jwan Al-doski, Shattri B. Mansor and Helmi Zulhaidi Mohd Shafri, *Image Classification in Remote Sensing*, Journal of Environment and Earth Science, ISSN 2224-3216 (Paper) ISSN 2225-0948 (Online) Vol. 3, No.10, 2013 , Retrieved from:
https://pdfs.semanticscholar.org/f5ed/fbb09d8f12c59017753f67160aa0c5af6588.pdf

ces, 189-204.