WASTE AND NATURAL DISASTER IMAGE CLASSIFICATION USING TRANSFER LEARNING

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ABSTRACT

Natural disasters can have a profound and wide-ranging influence on humans, affecting individuals, communities, and societies in numerous ways, encompassing physical, mental, economic, and social aspects. Classifying images of natural disasters using machine learning algorithms can offer significant assistance to humans in various ways by providing valuable insights and support in disaster management and response efforts. Annually, the Earth produces 2.01 billion metric tons of municipal solid waste, and at the very least, a very conservative estimate suggests that approximately 33 percent of this waste is not handled in an environmentally sound manner. Looking ahead to the future, it is anticipated that global waste production will reach 3.40 billion metric tons by 2050, which is more than double the rate of population growth during the same period [1]. Waste image classification has the potential to enhance waste management practices, increase recycling rates, reduce environmental pollution, and support sustainable development. A Convolutional Neural Network is a type of machine learning algorithm, more precisely, a type of artificial neural network specifically designed for tasks involving images and visual data. CNNs have revolutionized computer vision and image processing applications due to their ability to automatically learn and extract meaningful features from images. This compilation of contemporary research encompasses academic papers and articles addressing the diverse algorithms employed in the classification of images related to both natural disasters and waste. This literature review also includes papers discussing algorithms used in image classification and covers papers on convolution neural network.

Keyword : - *Natural disasters, waste, machine learning algorithms, image classification, CCN- convolution neural network*

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1. INTRODUCTION

In our rapidly changing world, the management of waste and the prediction of natural disasters have become critical challenges for humanity. Waste management, an ever-growing concern, not only poses environmental threats but also has social and economic implications. On the other hand, natural disasters, ranging from hurricanes and earthquakes to wildfires and floods, continue to wreak havoc, causing loss of life and extensive damage to property. Addressing these challenges necessitates innovative approaches, and one such method is the application of artificial intelligence and deep learning algorithms.

Convolutional Neural Networks (CNNs) have emerged as a powerful tool in the realm of computer vision, capable of extracting complex patterns and features from images and videos. This technology has been successfully employed in a multitude of applications, from image recognition and autonomous vehicles to medical diagnosis. In the context of waste management and natural disaster classification, CNNs offer a promising avenue for automating processes that were once dependent on manual labor and expert knowledge.

This paper offers literature insights into papers based on both natural disaster classification, waste management and also image processing. It also delves into CNN algorithm and discusses a few of the researches and articles published on the same.

2. MILESTONES

On the 8th of October, 2019, “A survey on data collection for machine learning: A big data—AI integration perspective” [2] was published by Y. Roh, G. Heo, and S. E. Whang. This paper explains two of the primary reasons why data collection has recently emerged as a critical concern. Firstly, with the increasing utilization of machine learning, we are encountering novel applications that may lack an adequate amount of labeled data. Secondly, unlike traditional machine learning, deep learning methods autonomously generate features, which reduces the need for manual feature engineering but may necessitate more substantial amounts of labeled data. This paper also undertakes a comprehensive examination of data collection from a data management perspective. Data collection predominantly encompasses three aspects: data acquisition, data labeling, and the enhancement of existing data or models. It also presents an overview of the research landscape surrounding these operations, offer recommendations on when to employ specific techniques, and pinpoint intriguing research challenges.

The article titled “Automatic detection of passable roads after floods in remote sensed and social media data” [3] authored by K. Ahmad, K. Pogorelov, M. Riegler, O. Ostroukhova, P. Halvorsen, N. Conci, and R. Dahyot was published in May, 2019. This paper tackles the complex task of classifying floods and detecting their aftermath by analyzing both social media content and satellite imagery. The automatic identification of disasters like floods remains a formidable challenge. The primary focus here is on determining which routes or roads remain usable during flooding incidents. The paper introduces two innovative solutions, which were specifically designed for two corresponding challenges in the MediaEval 2018 benchmarking competition. These challenges involve (i) recognizing images that offer evidence of road passability and (ii) distinguishing between passable and non-passable roads in images derived from two complementary information sources. For the first challenge, it relies on the features extracted from objects and scenes using various deep models that were pretrained on the ImageNet and Places datasets. These object and scene-level features are then using early, late, and double fusion techniques. To determine whether a road is navigable for vehicles in satellite images, Convolutional Neural Networks and a transfer learning-based classification strategy is employed.

The publication titled “Natural disasters detection in social media and satellite imagery: A survey” [4] by N. Said, K. Ahmad, M. Riegler, K. Pogorelov, L. Hassan, N. Ahmad, and N. Conci was released in November of 2019. In this paper, a comprehensive survey of the existing body of literature pertaining to the detection of disasters and the analysis of information retrieved from both social media and satellite sources is conducted. The literature on disaster detection and the analysis of multimedia content related to disasters, classified based on the nature of the content, can be divided into three main categories: (i) the identification of disasters in text; (ii) the analysis of disaster-related visual content sourced from social media; and (iii) the detection of disasters in satellite imagery. An extensive review of various approaches proposed within these three domains is conducted. Additionally, the benchmark datasets available for evaluating disaster detection frameworks are also explained. A comprehensive discussion on the insights derived from this literature review and identify forthcoming trends and challenges is also included.

The paper named “Social media and satellites,” [5] written by K. Ahmad, K. Pogorelov, M. Riegler, N. Conci, and P. Halvorsen, was released in February 2019. This paper introduces a system called JORD, which possesses the capability to autonomously gather social media data, including text analysis in local languages, related to technological and environmental disasters. JORD can also automatically link this social media data with remote-sensed information. Furthermore, to ensure the quality of the retrieved information, JORD incorporates a hierarchical filtering mechanism based on temporal data and content analysis of the multimedia information it collects. To demonstrate the system's capabilities, numerous instances of disaster events detected by JORD are presented. The quality of the information it provides about these events and the system's usefulness from the perspective of potential users, leveraging crowdsourcing methods is assessed and evaluated.

In 2020, the paper “Intelligent fusion of deep features for improved waste classification” [6] was published by K. Ahmad, K. Khan, and A. Al-Fuqaha. In this article, the challenge of automatically classifying waste materials based on images is tackled by introducing a novel approach called "double fusion". This approach intelligently combines multiple deep learning models using both feature-level and score-level fusion techniques. A total of six different fusion techniques are employed and compared, including two feature-level fusion methods: (i) Discriminant Correlation Analysis and (ii) simple concatenation of deep features. Additionally, four late fusion methods: (i) Particle Swarm Optimization, (ii) Genetic modeling of deep features, (iii) Induced Ordered Weighted Averaging, and (iv) a baseline method treating all deep models equally are explored.

X.-Y. Zhang, H. Shi, X. Zhu, and P. Li authored and published a paper titled “Active semi-supervised learning based on self-expressive correlation with generative adversarial networks.” [7] in June of 2019. This paper seeks to tackle these challenges by introducing a novel framework for robust and efficient model training. This framework leverages both labeled and unlabeled instances to their full potential and incorporates reliable synthetic instances for further enhancement. The paper introduces a method for estimating the correlation between instances, which helps uncover the underlying relationships among them. It presents a unique approach called “Active Semi-Supervised Learning with Generative Adversarial Networks” (ASSL-GANs). ASSL-GANs simultaneously maintain three key components: a generator, a discriminator, and a classifier. These components collaborate in both adversarial and cooperative ways to gain a comprehensive understanding of the entire data distribution. The entire architecture is trained end-to-end by optimizing loss functions associated with each component network in an alternating update fashion.

“A survey of active learning algorithms for supervised remote sensing image classification” [8] was a paper published in June of 2011 by D. Tuia, M. Volpi, L. Copa, M. Kanevski, and J. Munoz-Mari. This paper examines and evaluates the primary categories of active learning algorithms in the context of remote sensing: committee-based, large margin, and posterior probability-based. For each category, it explores the latest advancements within the remote sensing community and provides details and testing of various heuristics. The paper also considers challenging remote sensing scenarios, including tasks involving very high spatial resolution and hyperspectral image classification. The paper offers guidance for selecting the appropriate approach, particularly for new or less experienced users, to ensure the creation of an effective training dataset for remote sensing image classification.

An article was published in March of 2020, titled “Adversarial sampling for active learning” [9] by C. Mayer and R. Timofte. This paper introduces a novel active learning approach called ASAL, which utilizes a GAN-based method to generate high-entropy samples. Instead of directly annotating these synthetic samples, ASAL identifies and includes similar samples from an existing pool for training. ASAL also offers the advantage of a small runtime complexity (sub-linear) compared to traditional uncertainty sampling (linear). It also analyzes the conditions under which ASAL performs optimally and why it may sometimes face challenges in outperforming random sample selection.

In July of 2020, the paper “Active learning for hierarchical multi-label classification” [10] was published by F. K. Nakano, R. Cerri, and C. Vens. To address the selection of data points that would yield the most informative labels, active learning methods can be employed. Active learning (AL) is a subset of machine learning that focuses on building models using fewer but more representative instances. This study introduces a publicly available framework that includes both baseline and cutting-edge algorithms designed for this specific task. Additionally, a novel algorithm called Hierarchical Query-By-Committee (H-QBC) is proposed and evaluated on datasets from various domains.

The article titled “Event recognition in personal photo collections: An active learning approach” [11] authored by K. Ahmad, M. L. Mekhalfi, and N. Conci was published in 2018. In this paper, an active learning approach for event recognition in personal photo collections to address challenges stemming from weakly labeled data and the presence of unrelated pictures in these collections is introduced. Traditional methods that rely on supervised learning often struggle to distinguish relevant samples in training albums, resulting in erroneous classifications. This approach aims to leverage active learning principles to select the most pertinent samples from a collection for classifier training. The significance of relevant images in the event recognition process is explored and the deterioration of performance is illustrated when all images, including irrelevant images, are included.

The publication titled “Active learning for event detection in support of disaster analysis applications” [12] by N. Said, K. Ahmad, N. Conci, and A. Al-Fuqaha was released in 2019. The analysis of disasters within social media content is a compelling area of research due to the wealth of available data. However, there is a notable absence of labeled data that can be employed to train machine learning models for disaster analysis applications. Active learning emerges as a potential solution to this challenge. This paper introduces and evaluates the effectiveness of an active learning-based framework designed for disaster analysis using images shared on social media platforms. Specifically, the performance of various active learning techniques that employ different sampling and disagreement strategies is assessed. Additionally, a comprehensive dataset comprising images related to eight common types of natural disasters is compiled.

The paper named “Context aware image annotation in active learning,” [13] written by Y. Sun and K. Loparo, was released in 2020. Although various methods, including automatic and semi-automatic labeling, have been suggested to reduce labeling costs, a decrease in the number of labeled instances doesn't necessarily lead to cost reduction. This is because the most valuable queries for the learning process may involve the most challenging or ambiguous cases, which are consequently more expensive for an expert annotator to label accurately. This paper aims to address this issue by leveraging image metadata to provide additional information to the annotator during the annotation process. A framework called Context Aware Image Annotation Framework (CAIAF) is introduced, which utilizes image metadata as a similarity metric to group images for annotation. Furthermore, relevant metadata details is presented as context for each image within the annotation interface.

In March of 2020, the paper “Pair-based uncertainty and diversity promoting early active learning for person re-identification” [14] was published by W. Liu, X. Chang, L. Chen, D. Phung, X. Zhang, Y. Yang, and A. G. Hauptmann. This paper addresses a practical and demanding problem known as "Early Active Learning," which comes into play during the initial stages of experiments when no pre-labelled samples are available as references for human annotators. Existing early active learning methods for Re-ID face two key limitations. First, these methods focus on selecting individual instances rather than pairs, potentially missing out on optimal pairs for Re-ID. Second, many of these methods primarily consider instance representativeness, which may result in the selection of less diverse and less informative pairs. To overcome these limitations, a novel pair-based active learning approach for Re-ID is introduced. This algorithm chooses pairs, rather than individual instances, from the entire dataset for annotation. In addition to representativeness, considerations of uncertainty and diversity in terms of pairwise relationships are incorporated. As a result, this algorithm is capable of identifying the most representative, informative, and diverse pairs for annotating Re-ID data.

G. T. Ngo, T. Q. Ngo, and D. D. Nguyen authored and published a paper titled “Image retrieval with relevance feedback using SVM active learning” [15] in December of 2016. Generally, relevance feedback aims to enhance retrieval performance by learning from user judgments on the retrieved results. Despite widespread interest in feedback-related technologies, they often encounter certain limitations. One of the most notable limitations is the need for users to go through multiple iterations before obtaining improved search results. This can make the process inefficient and cumbersome for online applications. This paper proposes an efficient feedback-related approach for content-based image retrieval. Initially, a Support Vector Machine is employed to learn a decision boundary for filtering images in the database. Subsequently, a ranking function is calculated to select the most informative samples. This ranking function is established based on a novel criterion that takes into account both the scores of the Support Vector Machine function and the similarity metric between the "ideal query" and the images within the database.

“Multicriteria active deep learning for image classification” [16] was a paper published in May of 2019 by J. Yuan, X. Hou, Y. Xiao, D. Cao, W. Guan, and L. Nie. With regard to deep learning techniques (e.g., CNN) and their applications (e.g., image classification), labeling work is of great significance as training processes for obtaining parameters in neural networks which requires abundant labeled samples. Although a few active learning algorithms have been proposed for devising certain straightforward sampling strategies (e.g., density, similarity, uncertainty, and label-based measure) for deep learning algorithms, these employ onefold sampling strategies and do not consider the relationship among multiple sampling strategies. To this end, a novel solution “multi-criteria active deep learning” (MCADL) is devised to learn an active learning strategy for deep neural networks in image classification. The sample selection strategy selects informative samples by considering multiple criteria simultaneously (i.e., density, similarity, uncertainty, and label-based measure). Moreover, this approach is capable of adjusting weights adaptively to fuse the results from multiple criteria effectively by exploring the utilities of the criteria at different training stages.

An article was published in July of 2020, titled “Hyperspectral image classification with convolutional neural network and active learning” [17] by X. Cao, J. Yao, Z. Xu, and D. Meng. To enhance classification performance while mitigating the labeling expenses, this article introduces an active deep learning approach for HSI classification that combines active learning and deep learning within a unified framework. Firstly, a convolutional neural network (CNN) is trained using a limited set of labeled pixels. Subsequently the most informative pixels are actively selected from a candidate pool for labeling. Following this, the CNN is fine-tuned using the new training set that incorporates the newly labeled pixels. These two steps are carried out iteratively. Finally, a Markov random field (MRF) is employed to ensure smooth class label transitions, further improving classification performance.

In 2020, the paper “Hyperspectral image classification based on active learning and spectral-spatial feature fusion using spatial coordinates” [18] was published by C. Mu, J. Liu, Y. Liu, and Y. Liu. Typically, spatial information is introduced in an unsupervised or complex manner. However, in this work, this paper proposes a straightforward supervised approach that utilizes spatial coordinates as spatial information, leading to the development of two HSI classification algorithms. The first algorithm, known as HSI Classification Based on Spectral-Spatial Feature Fusion using Spatial Coordinates (SSFFSC), combines spectral and spatial features by dividing the HSI into multiple smaller images in the spatial dimension. Samples within each small image are randomly selected as training data, and a Support Vector Machine (SVM) is employed to classify these samples based on their spatial coordinate and spectral features. The resulting probability features are further processed by SVM to obtain the final classification outcome. Recognizing that the performance of SSFFSC depends on the partitioning of HIS, this approach is extended by incorporating active learning (AL) to create a new method called HSI Classification Based on Active Learning and SSFFSC (SSFFSC-AL). In SSFFSC-AL, we eliminate the need for HSI partitioning, and training samples are selected adaptively using AL's sampling scheme.

The article titled “Human Activity Recognition Using Convolutional Neural Networks” [19] authored by Gulustan Dogan, Sinem Sena Ertas, and İremnaz Cay was published in October 2021. This research introduces a deep learning method based on sensor data for the purpose of recognizing human activities. The proposed approach relies on linear accelerometer (LAcc), gyroscope (Gyr), and magnetometer (Mag) sensors to detect eight different transportation and movement activities. These activities encompass Still, Walk, Run, Bike, Bus, Car, Train, and Subway. To carry out this investigation, the Sussex-Huawei Locomotion (SHL) Dataset is employed, which involves data from three participants, to discern the physical activities of users. The Fast Fourier Transform (FFT) spectrograms generated from the three axes of LAcc, Gyr, and Mag sensor data is used as the input for the Convolutional Neural Network (CNN) model.

The publication titled “Convolutional Neural Network (CNN) for Image Detection and Recognition” [20] by Rahul Chauhan, Kamal Kumar Ghanshala, and R.C Joshi was released in December 2018. Deep Learning algorithms are crafted to emulate the functioning of the human brain's cortex. These algorithms manifest as deep neural networks, which comprise numerous concealed layers. Among these deep learning algorithms, Convolutional Neural Networks (CNNs) stand out as they have the capacity to train on extensive datasets featuring millions of parameters, using 2D images as input and applying filters to produce the desired results. In this article, CNN models are constructed to assess their effectiveness in handling image recognition and detection tasks. The algorithm on the MNIST and CIFAR-10 datasets are implemented and its performance is assessed.

In December of 2017, the paper “Application of deep convolution neural network” [21] was published by Jiudong Yang, and Jianping Li. Before the advent of CNNs, both image processing and speech recognition heavily relied on traditional machine learning algorithms. Although these conventional approaches yielded significant achievements, further progress became challenging to attain, prompting the development of CNNs. The triumph of CNNs in image processing and speech recognition has ignited a surge of research interest in applying them to natural language processing. In the context of natural language processing, CNNs have found widespread utility, albeit with room for improvement in their performance. This paper aims to provide a clearer exposition of the CNN structure while also offering a concise overview and outlook on ongoing CNN research in image processing, speech recognition, and natural language processing.

Arohan Ajit, Koustav Acharya, and Abhishek Samanta authored and published a paper titled “A Review of Convolutional Neural Networks” [22] in February of 2020. Prior to the widespread adoption of Convolutional Neural Networks (CNNs), computer recognition tasks necessitated the extraction of features from the given data, a process that often lacked efficiency and did not yield a high level of accuracy. However, in recent times, CNNs have emerged as a solution aimed at significantly improving both efficiency and accuracy across various domains, with notable applications in Object Detection, as well as Digit and Image Recognition. CNNs operate based on a well-defined algorithmic process, which includes crucial steps such as Backpropagation, Convolutional Layers, Feature Extraction, and Pooling. Additionally, this article will delve into the utilization of different frameworks and tools associated with CNN models.

“A Review of Convolution Neural Network Used in Various Applications” [23] was a paper published in October of 2021 by Parul Choudhary, and Pooja Pathak. The deep learning technique known as Convolutional Neural Networks (CNN) proves highly effective at automatically detecting features within images. CNNs have the capability to train on vast datasets containing billions or millions of parameters, taking images as input and convolving them with specific filters to generate desired outputs. CNNs find applications in diverse fields, including image recognition, image classification, and image detection. This paper offers a comprehensive review of the literature on CNNs applied across various domains, including medicine, agriculture, and document layout. Furthermore, it discusses the development of numerous CNN models designed to assess their performance in image detection and recognition tasks. Consequently, this paper conducts a comparative analysis of these models in relation to the datasets used, with the aim of providing valuable guidance to newcomers in this domain.

An article was published in October of 2018, titled “Object Detection Using Convolutional Neural Networks” [24] by Reagan L. Galvez, Argel A. Bandala, Elmer P. Dadios, Ryan Rhay P. Vicerra, and Jose Martin Z. Maningo. Recent advancements in deep neural networks applied to image processing have now made it feasible to accurately classify and detect objects. In this research paper, Convolutional Neural Networks (CNNs) are employed for object detection within the robot's surroundings. The study compares two state-of-the-art models for this purpose: the Single Shot Multi-Box Detector (SSD) with MobileNetV1 and the Faster Region-based Convolutional Neural Network (Faster-RCNN) with InceptionV2. The results indicate that one of these models is well-suited for real-time applications due to its speed, while the other excels in achieving more precise object detection.

In November of 2018, the paper “Advancements in Image Classification using Convolutional Neural Network” [25] was published by Farhana Sultana, Abu Sufian, and Paramartha Dutta. Convolutional Neural Networks (CNNs) represent the cutting-edge technology in the field of image classification. This paper provides a concise overview of the various components that constitute a CNN. Furthermore, it presents a comprehensive discussion of diverse CNN architectures designed specifically for image classification. Over the course of this paper, the evolution of CNNs is demonstrated, starting from the LeNet-5 model to the most recent SENet model. The exploration has encompassed detailed descriptions of each model and insights into their training processes. Additionally, a comparative analysis has been conducted among these models to highlight their respective strengths and weaknesses.

The article titled “Transfer learning-based Object Detection by using Convolutional Neural Networks” [26] authored by Bulbul Bamne, Neha Shrivastava, Lokesh Parashar, and Upendra Singh was published in July 2020. Object detection has gained significant importance in various aspects of our daily lives. Earlier, machine learning techniques were employed for this task, primarily focusing on image-based species classification to extract relevant feature sets. This process of feature extraction is crucial for achieving successful object detection. In order to address the challenges associated with object classification, this research introduces a deep learning approach based on transfer learning. The study investigates various convolutional neural networks (CNNs) and employs a majority voting scheme to enhance the outcomes.

The publication titled “Deep Convolutional Neural Network Transfer Learning Optimization Based on Visual Interpretation” [27] by Yibo Xu, Jiongming Su, Fengtao Xiang, Ce Guo, Haoran Ren, and Huimin Lu was released in July 2021. In image classification tasks, training deep convolutional neural networks typically demands a substantial volume of data. Given the practical constraints of environmental limitations, resource availability, and time constraints, it becomes highly valuable to achieve higher recognition accuracy with a reduced number of training samples in the shortest possible duration. To address this challenge, a specific image classification task benefits from a novel optimization approach based on visual interpretation within a deep convolutional neural network transfer learning framework. Firstly, the method utilizes class activation mapping visualization as a visual interpretation tool, generating class activation heat maps for the validation set images. This allows for an in-depth analysis of the reasons behind misclassification in these images. Secondly, a "feedback" mechanism is introduced, involving pre-recognition and visualization of an optimized dataset using a model initially trained on the original dataset. This step aims to identify the images that exert the most significant influence on enhancing recognition accuracy, thereby maximizing their impact on the original model. Finally, the model undergoes retraining on the optimized training set. Experimental results demonstrate the efficacy of this approach in significantly improving the recognition accuracy of the transfer learning model for image classification.

3. CONCLUSION

Based on the papers published and the studies done it can be safely said that integrating machine learning techniques for classifying images of natural disasters can significantly enhance disaster management and response capabilities by providing real-time information, improving situational awareness, and aiding in decision-making processes. Using machine learning in waste classification can contribute to more efficient and effective waste management systems, benefiting both the environment and human communities. Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for processing and analyzing visual data, such as images and videos. CNNs have been incredibly successful in various computer vision tasks, including image classification, object detection, image segmentation, and more. Their hierarchical feature extraction and ability to learn complex patterns make them a powerful tool for incorporation into systems involving image classification. The potential of CNN algorithms in automation of natural disasters and waste image classification is very high and can assist in reducing the time while increasing the accuracy of the system.

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