Early Detection of Wildfire

1st Tobias Tobias
dept. Computer Science and Multimedia
University of Alberta
Edmonton, CA
ttobias@ualberta.ca
ORCID[0009-0004-3545-1749]

2nd Sanjana Sanjana
dept. Computer Science and Multimedia
University of Alberta
Edmonton, CA
ssanjana@ualberta.ca
ORCID[0009-0009-2019-4432]

3rd Swati Chowdhury
dept. Computer Science and Multimedia
University of Alberta
Edmonton, CA
schowdh4@ualberta.ca
ORCID[0009-0003-7020-9635]

***Abstract*—Addressing to the increasing wildfire in Alberta and other parts of Canada has become a challenge according to government of Canada. The budget has increased from 800 million to 1.4 billion Canadian dollar annually over the past 10 years[1]. According to MNP LLP report the wildfires experienced only by Alberta in 2015 has been twice the amount experienced in 1990 which is becoming substantially expensive[2]. Distinguishing wildfires from environmental factors like smoke, dust, haze, mist, and fog using conventional computer vision methods is a complex task. This research proposal explores the efficacy of Convolutional Neural Networks (CNN) and Image Enhancement techniques for early wildfire detection, building upon recent advancements in Pixel Distribution Learning (PDL) methods used in background subtraction[3]. By combining these techniques, image datasets will be enhanced, enabling to detect wildfire and classify them more efficiently.**

***Index Terms*—Forest fire, early detection, CNN, pixel distribution learning**

I. Introduction

Wildfires represent a pressing concern in Alberta, demanding effective measures for early detection to curtail their spread and mitigate the associated impact on communities and ecosystems. The current annual expenditure to combat wildfires stands at approximately 1 billion Canadian dollar, underscoring the urgency of advancing detection methodologies. Differentiating between genuine smoke wildfire indicators and atmospheric elements like cloud, dust, haze, land, and seaside remains challenging due to the intricate nature of real-world fire scenarios.

This proposal seeks to investigate the potential of employing CNN and image enhancement techniques for early wildfire detection, addressing the limitations of existing methodologies. Inspired by recent strides in PDL methods applied to background subtraction, this research will delve into leveraging this approach to heighten classification accuracy for early wildfire detection. The fusion of CNN with image enhancement techniques followed by PDL will enrich image datasets, facilitating more precise classification and thereby improving wildfire detection (Fig. 1).

This study aims to compare the accuracy of this technique against traditional wildfire detection methods. Additionally, this research will leverage the USTC SmokeRS dataset[4] ,a comprehensive satellite based image dataset for smoke scene detection based on Moderate Resolution Imaging Spectroradiometer (MODIS) data. This dataset comprises 6225 RGB images across six classes, including Cloud, Dust, Haze, Land, Seaside, and Smoke, each with a spatial resolution of 1 km. The dataset's utilization for fire smoke detection and recognition of aerosol classes significantly enhances the model's ability to identify early signs of wildfires, ultimately bolstering the efficiency of early detection systems and contributing to mitigating wildfire-related risks.

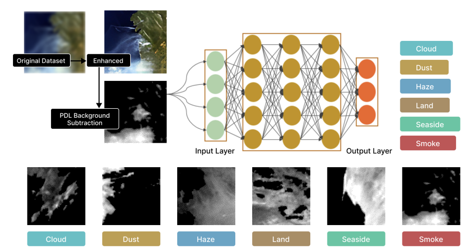


Fig. 1. CNN Classification with PDL Background Subtraction

The envisioned outcomes of this research are poised to significantly detect early wildfire issues particularly in the Alberta and BC regions. Leveraging CNNs in conjunction with PDL techniques for analysing satellite imagery data will enable the early detection of wildfires, distinguishing between smoke and various atmospheric conditions. Evaluation metrics beyond classification accuracy, including precision, recall, and F1 score, will be employed to comprehensively assess the success of this approach.

In conclusion, this research endeavour holds substantial promise for positively impacting society by significantly improving the accuracy of early wildfire detection, thereby enhancing the safety of communities, critical infrastructure and ecosystems.

II. Existing Approach

A. Only detect Fire or No Fire [5]

This existing approach uses convolutional neural networks (CNNs) with the GoogleNet architecture to differentiate between images of fire and no fire from home surveillance cameras. However, a surveillance camera cannot cover a large area in the forest. Even if it could, the fire would already be present, and early detection would not be possible.(Fig. 2)

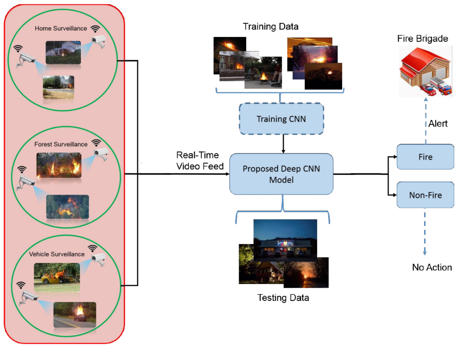


Fig. 2. Existing Approach 1

B. *Only detect Smoke or No Smoke* [6]

This approach is classifying forest fire smoke in real time using deep convolutional neural network comparing between EfficientDet, Faster R-CNN, YOLOv3, SSD, and advanced CNN. However, the forest fire smoke has its special nature, a real forest fire smoke data set is hard to obtain through this experiment, due to which it may reduce the robustness and effectiveness of the trained model in recognizing forest fire smoke scenes that are not included in the training set. Thus, the real-life smoke detection is still challenging in their approach.(Fig. 3)

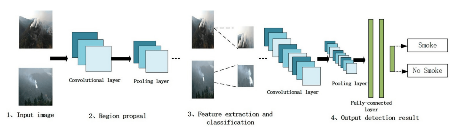


Fig. 3. Existing Approach 2

III. Our Approach

A. *Pre - Processing of Data*

Since the satellite image quality might not clear enough to detect small smoke particles. In the first step we will enhance the image using Generative AI.(Fig. 4)

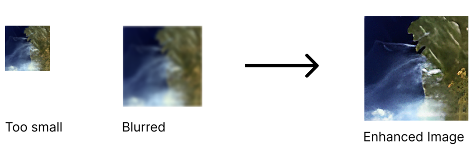


Fig. 4. Image Enhancement

B. *Clustering*

In this second step, we will cluster the pre-processed images using CNN classification.(Fig. 5)

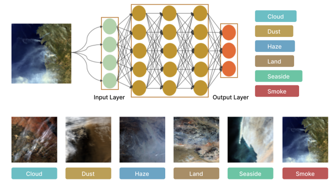


Fig. 5. Clustering

C. *Background Subtraction*

In this third step, we will subtract the data set image object from its background using Deep Pixel Distribution to clearly identify the cloud, dust, haze, land, seaside, and smoke.(Fig. 6)

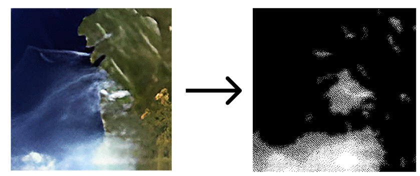


Fig. 6. Background Subtraction

D. *Classifying the Background Subtracted Images*

After that we will use CNN to classify the images obtained from the Pixel Distribution Learning Background Subtraction.(Fig. 7)

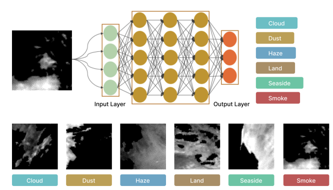
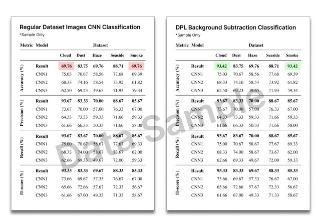


Fig. 7. Classifying the Background Subtracted Images

E. *Result Preparation*

Lastly, we will compare the result from Regular Data set Images and Deep Pixel Distribution Background Subtraction Classification, with Accuracy, Precision, Recall, F1 score as the comparison matrix.(Fig. 8)



Regular Dataset Images CNN Classification
*Sample Only

Metric	Model	Cloud	Dust	Haze	Seaside	Smoke
Accuracy (%)	**Result**	**69.76**	**83.75**	**69.76**	**88.71**	**69.76**
	CNN1	75.03	70.67	58.56	77.68	69.39
	CNN2	68.33	74.16	58.54	73.92	61.82
	CNN3	62.50	69.23	49.65	71.93	59.34
Precision (%)	**Result**	**93.67**	**83.33**	**70.00**	**88.67**	**85.67**
	CNN1	73.67	70.00	57.00	76.33	67.00
	CNN2	64.33	73.33	59.33	71.66	59.33
	CNN3	61.66	66.33	50.33	71.66	58.00
Recall (%)	**Result**	**93.67**	**83.67**	**70.00**	**88.67**	**85.67**
	CNN1	75.00	70.67	58.67	77.67	69.33
	CNN2	68.33	74.00	58.67	73.67	62.00
	CNN3	62.66	69.33	49.67	72.00	59.33
f1-score (%)	**Result**	**93.33**	**83.33**	**69.67**	**88.33**	**85.33**
	CNN1	73.66	69.67	57.33	76.67	67.00
	CNN2	65.66	72.66	57.67	72.33	56.67
	CNN3	61.66	67.00	49.33	71.33	58.67

DPL Background Subtraction Classification
*Sample Only

Metric	Model	Cloud	Dust	Haze	Seaside	Smoke
Accuracy (%)	**Result**	**93.42**	**83.75**	**69.76**	**88.71**	**93.42**
	CNN1	75.03	70.67	58.56	77.68	69.39
	CNN2	68.33	74.16	58.54	73.92	61.82
	CNN3	62.50	69.23	49.65	71.93	59.34
Precision (%)	**Result**	**93.67**	**83.33**	**70.00**	**88.67**	**85.67**
	CNN1	73.67	70.00	57.00	76.33	67.00
	CNN2	64.33	73.33	59.33	71.66	59.33
	CNN3	61.66	66.33	50.33	71.66	58.00
Recall (%)	**Result**	**93.67**	**83.67**	**70.00**	**88.67**	**85.67**
	CNN1	75.00	70.67	58.67	77.67	69.33
	CNN2	68.33	74.00	58.67	73.67	62.00
	CNN3	62.66	69.33	49.67	72.00	59.33
f1-score (%)	**Result**	**93.33**	**83.33**	**69.67**	**88.33**	**85.33**
	CNN1	73.66	69.67	57.33	76.67	67.00
	CNN2	65.66	72.66	57.67	72.33	56.67
	CNN3	61.66	67.00	49.33	71.33	58.67

Fig. 8. Result Preparation

IV. Literature Review

Uncontrolled wildfires, which are natural phenomena, have inflicted substantial harm on both human communities and the natural environment. Numerous researchers have developed fire detection models by employing advanced deep learning techniques. These applications leverage a variety of computer vision methods and models for the analysis of images and videos. In this literature review, we delve into diverse research endeavors focused on the creation of various models utilizing a range of techniques.

In one research, the authors address the utilization of deep learning for background subtraction. They assess prior methods for background subtraction, delineate their limitations, and propose an innovative technique named Dynamic Deep Pixel Distribution Learning (D-DPDL). D-DPDL harnesses a convolutional neural network to acquire knowledge about the statistical distribution of pixels. They empowers D-DPDL to more effectively characterize the background and eliminate foreground objects. Through evaluation on established benchmarks, the authors substantiate that D-DPDL surpasses prevailing methods.[7]

In a related article, a fully automated system for tracking smoke is presented. It explores the integration of deep image quality enhancement and an adaptive level set model. The authors introduce an architecture based on convolutional autoencoders (CAE) designed to eliminate noise and reconstruct images. Their study establishes the superiority of this approach over other denoising methods. The enhanced image quality significantly enhances the analysis of reconstructed video images.[8]

In another research endeavor, the authors introduce an early detection method for forest fires employing deep learning techniques. They underscore the significance of forests and the imminent threat of forest fires. Their proposed approach involves the deployment of image recognition and convolutional neural networks (CNNs) to enable early detection. The authors fine-tuned the Resnet50 architecture and incorporated additional convolutional layers, achieving remarkable training set accuracy (92.27 percent) and test accuracy (89.57 percent).[9]

Another comprehensive article focuses on the application of deep learning in the detection of wildfires from satellite images. It discusses the considerable challenges associated with wildfire detection, including the imperatives of timely and accurate identification. The authors put forth a novel deep learning model that excels on multiple metrics, capable of detecting wildfires in both daylight and nocturnal images while demonstrating resilience in the face of cloud cover.[10]

Another article delves into the domain of wildfire detection, emphasizing the dearth of data and the intricacy of identifying smaller objects. The authors propose a method utilizing generative adversarial networks (GANs) for the creation of synthetic wildfire images. They employ a weakly supervised object localization (WSOL) approach to annotate these images. The presented method surpasses other methodologies across a range of performance metrics.[11]

The realm of wildfire forecasting is explored in some articles, underlining the vital need for such predictions on a global scale. The authors establish a global fire dataset and employ deep learning techniques to predict the presence of burned areas. The model demonstrates impressive capabilities by forecasting burned areas at varying time horizons, from 8 to 64 days in advance. That research underscores the potential of deep learning for global-scale wildfire forecasting.[12]

In a related article, the authors focus on the early detection of forest fires using satellite imagery and deep learning models. This study highlights the importance of forest conservation and the threats posed by both natural and human-induced calamities. The proposed method achieves an impressive accuracy of 98.46 percent, enhancing the prospects for early forest fire detection.[13]

The other article addresses the challenge of smoke image segmentation in low-light conditions, presenting a novel approach to tackle this issue. The proposed method incorporates two sequential networks: an image enhancement network and a smoke segmentation network. The image enhancement network is instrumental in improving the visibility of smoke features in low-light conditions, enabling the subsequent smoke segmentation network to perform more accurately. The results indicate that this method outperforms alternatives on both public and real-world datasets.[14]

In a study focused on satellite-based smoke detection, the authors emphasize the urgency of early smoke detection and the difficulties associated with using satellite imagery. They introduce the SmokeNet model, which incorporates spatial and channel-wise attention mechanisms to enhance smoke detection. SmokeNet surpasses other state-of-the-art methods, demonstrating its effectiveness on the USTCSmokeRS dataset.[15]

Furthermore, that particular review presents a novel optical flow based encoder-decoder network, FUNet, tailored for video background subtraction, particularly in scenarios involving motion blur. FUNet combines traditional optical flow estimation with convolutional neural networks, utilizing optical flow to capture motion-related features between frames. These motion features are integrated with the original frame's appearance and fed into a UNet-like encoder-decoder architecture for the prediction of foreground masks. The model's training on a newly developed video segmentation dataset, established by the authors, yields remarkable results, with a high average Dice coefficient of 0.96 on test videos. The FUNet model and dataset are designed to enhance video background subtraction, with potential applications in video conferencing and virtual reality by effectively addressing motion blur challenges through the integration of optical flow features alongside an encoder-decoder architecture.[16]

A related study evaluates four neural network models (fully connected, 1D CNN, 2D CNN, and 3D CNN) using recall, accuracy, and F1 scores through cross-validation. It aims to detect and manage wildfires from hyperspectral imagery obtained from PRISMA. The results show that the fully connected model outperformed the 3D CNN in classification accuracy, while the 3D model offered more nuanced but less distorted classifications. However, all models have room for improvement, particularly with more complex models and a larger dataset to reduce false alarms.[17]

Some of the research introduces a wildfire detection system using a novel convolutional neural network (FireCNN) for real-time analysis of Himawari-8 satellite imagery. It enables faster training and accurate extraction of fire spot characteristics. Different spectral bands are used to distinguish water, clouds, and potential fire spots to reduce false alarms. However, it has limitations due to the small training and testing datasets and the introduction of artificial environmental information for feature enhancement.[18]

Other research focuses on forest fire detection and proceeds in distinct phases. It starts with deep neural networks using random weight initialization, then employs deep networks with ImageNet weights. Fine-tuning with ImageNet data enhances their performance. Finally, a combination of machine learning and deep learning methods is used. The study utilizes the FLAME dataset from a pine forest fire in Flagstaff, Arizona, assessing nine models, including pre-trained CNNs and hybrid approaches, based on training, validation, computational time, and testing accuracy.[19]

A related study focuses on early wildfire detection and mitigation using deep learning and UAV-based remote sensing technology. UAV drones provide real-time imagery in complex forest environments. The research utilizes deep learning methods, including smoke and flame image classification, object detection, and semantic segmentation, to process UAV images effectively. Notably, object detection demonstrates high accuracy. While these algorithms haven't been extensively tested on UAV images, there is optimism that the use of Generative Adversarial Networks (GANs) will address limited testing dataset challenges in the future.[20]

Another research focuses on the detection and protection of the Amazon Forest in the Amazonia region. Deep Convolutional Neural Networks (CNNs) are used to analyze satellite image patterns collected from various sources, including the MultiEarth dataset, VIIRS, MODIS, Sentinel, and Landsat satellites. The image segmentation architecture utilizes multimodal remote sensing images as the input dataset. These images undergo an encoding and decoding process with EfficientNet, interconnected through skip connections. This process yields a binary mask with pixel values of 0 or 1, indicating the presence or absence of a fire situation with a pixel-wise AUC of 0.95.[21]

A similar research introduces a fire detection system based on SqueezeNet, designed to be computation-friendly and accurate in reducing false alarms. Two benchmark datasets and a real-time CCTV network are employed to demonstrate fire detection and localization of surveilled objects.[22]

A related paper presents a framework for the challenging task of detecting unpredictable flames with varying shapes, colors, and textures. It utilizes a Convolutional Neural Network (CNN) and selects candidate flames based on properties like dynamics and color. The two-stage object detection framework initially identifies regions of interest (RoIs) for any object, followed by classification of objects and bounding box regression based on these RoIs, resulting in an effective flame detection system.[23]

Some other research showcases real-time and precise wildfire monitoring using a U-Net model, integrating datasets from Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 MultiSpectral Instrument (MSI) data. The model is trained using Continuous Joint Training (CJT) and Learning without Forgetting (LwF) methodologies, which allow the incorporation of both historical training data and newly acquired data, ensuring a stable and comprehensive wildfire monitoring process. [24]

In some papers, fire image classification is approached using a traditional handcrafted method, Support Vector Machine (SVM). SVM leverages Higher-Order Statistics (HOS) cumulant features to differentiate between fire and non-fire pixels, reducing computational complexity. Preliminary tests indicate slightly improved precision, sensitivity, recall, and F-measure values compared to random classifiers.[25]

The related paper explores an efficient method for fire and smoke detection in IoT (Internet of Things) applications using the FireNet network. FireNet, a lightweight network designed from scratch, aims to replace traditional physical fire detection systems on IoT platforms like Raspberry Pi. It demonstrates excellent performance in terms of accuracy, recall, and F-measure on standard and newly customized fire datasets, providing real-time visual feedback and alerts.[26]

In a paper,it outlines an image recognition algorithm for forest fires based on CNN. The distinctive aspect is the use of flame images for both training and testing. The paper introduces the AlexNet model and presents an adaptive pooling technique that combines color features to address potential limitations of traditional CNN pooling methods that might diminish image features in certain situations. The modified CNN pooling is employed for forest image recognition, and the paper discusses plans for future developments, including in-depth analysis of recognition rates and processing times in comparison to other algorithms.[27]

The authors of some related study have suggested the utilization of deep learning through Convolutional Neural Networks (CNNs) to detect wildfires in images captured by cameras. Given the significant challenges posed by wildfires and the imperative need for timely detection and response to safeguard human well-being and natural assets, their goal is to identify a CNN framework that offers the utmost accuracy in wildfire detection while optimizing computational efficiency. To achieve this, they have assembled a substantial dataset containing both wildfire and clean images and conducted extensive testing and validation of CNNs with various configurations of convolutional, pooling, and fully connected layers.[28]

An almost similar paper conducts a comprehensive survey of various fire detection datasets categorized by their composition methods and the devices used for data collection, including satellites, UAVs, and geodata. These datasets encompass diverse types of samples, such as images and videos. The study includes a comparative analysis of cutting-edge techniques, primarily focusing on their performance in detecting fire incidents within images and videos. The research emphasizes deep learning models, specifically those employing common CNN architectures like U-Net, AlexNet, GoogleNet, and YOLO (You Only Look Once), as well as studies utilizing R-CNN and ANN for the development of wildfire detection systems.[29]

In a related study, CNN technology is employed to detect natural disasters using real-time imagery sourced from satellites and drones. The CNN model serves the purpose of identifying these natural disasters, subsequently alerting relevant authorities, and assisting in minimizing potential damage.[30]

Some other research focuses on detecting forest wildfires by combining digital image processing, machine learning, and deep learning techniques. The research divides the forest wildfire detection task into two modules: wildfire image classification using Reduce-VGGnet and wildfire region detection employing an optimized CNN model.[31]

Another study introduces diverse techniques to propose distinctive grading frameworks for forest fires and smoke, enabling both their localization and severity assessment. The authors have presented a supervised fire-segmentation model reliant solely on image-level labels to precisely identify affected areas. To enhance efficiency, they have streamline the Faster CNN's complexity using a distillation approach. Their method outperforms existing CNN-based models, achieving detection and segmentation accuracy of 98.6 Percent compared to 68.2 Percent, all while maintaining a low latency of just 150ms, showcasing a remarkable balance between detection efficacy and speed. Additionally, they have developed a rapid fuzzy assessment method to gauge the extent of forest fire smoke.[32]

In one research, the authors have delved into the domain of transfer learning, utilizing pre-trained models for forest fire and smoke detection. Their approach was to involve extracting features and fine-tuning these models. The outcomes demonstrated that the Exception-based model outperformed all others, achieving an impressive 98.72 Percent accuracy. Additionally, they have explored techniques like LwF to preserve old dataset characteristics, outperforming mere feature extraction.[33]

That study contributes to the existing knowledge by assessing the effectiveness of an efficient solution for detecting wildfires and smoke, utilizing ensembles of multiple convolutional neural network architectures in a two-stage process. The proposed architecture combines the YOLO framework with two weight sets within a CNN ensemble. The system operates through two stages: if the CNN identifies anomalies in the frame, the YOLO architecture pinpoints the location of smoke or fire. The tasks addressed encompass classification and detection. The model's weights achieved commendable results during both training and testing phases. The classification model attained a 0.95 F1-score, 0.99 accuracy, and 0.98 sensitivity, employing a transfer learning approach.[34]

Some other study introduces a Convolutional Neural Network (CNN) model based on deep learning for forest fire detection. The process involves techniques like Image Collection, Pre-processing, and Image Classification. Initially, the dataset's images undergo preprocessing and are then passed through the CNN for feature extraction and detection. Additionally, a hardware setup using a Raspberry Pi is established to transmit alerts in the form of emails, buzzer alerts, and LCD displays to relevant authorities. The research attains an overall accuracy of 92.20 percent through the validation of the image set. Future extensions could involve incorporating Global Positioning System (GPS) to pinpoint the precise fire emergence location.[35]

Another paper introduces a fire detection system that relies on an ensemble of experts, utilizing information related to color, shape, and flame motion. The system's performance is rigorously evaluated using a comprehensive database, focusing on sensitivity and specificity. Experimental results confirm the effectiveness of the MES approach, which excels in achieving a superior true positive rate compared to its individual components. Notably, the approach significantly reduces false positives, dropping from 29.41 Percent to 11.76 Percent.[36]

From the above literature reviews, it is clear that deep learning has become the dominant approach for background subtraction and smoke/fire detection, outperforming traditional techniques. Key innovations include end-to-end pixel distribution learning, optical flow integration, and data augmentation. However, gaps persist in occlusion and incorporating meteorological and spatiotemporal data. Further research should explore recurrent networks, multimodal fusion, and attention mechanisms to address these limitations. Deep learning shows strong potential for early warning and disaster monitoring if techniques can be refined.

V. Challenges for Us

Currently we are using USTC SmokeRS data set, which is a comprehensive satellite-based image dataset for smoke scene detection based on Moderate Resolution Imaging Spectroradiometer (MODIS) data. However, we still searching for other labelled data set to improve the accuracy of this algorithm.

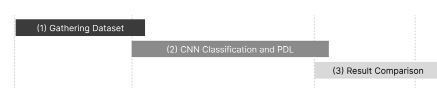


Fig. 9. Milestones

In this project we are using CNN classification for image clustering and Pixel Distribution Learning to remove the background of the images to early detection of wildfires, distinguishing between smoke and various atmospheric conditions with more precision but still we are studying the feasibility of combining these two concepts in this project to make a better algorithm which can be more efficient over the existing traditional algorithms.

We will compare the results of the regular data set image classification and PDL background image subtraction classification with Accuracy, Precision, Recall, and F1 Score as the comparison matrix.

VI. Our Work Explanation

Our work commenced with the extraction of the dataset from the USTC dataset, which was subsequently meticulously partitioned into training and validation sets. Following this, we uploaded the dataset to Kaggle.com to facilitate easy accessibility. Once uploaded, we initiated the CNN classification process for the unenhanced images, evaluating key metrics such as training loss, training accuracy, validation loss, and validation accuracy.

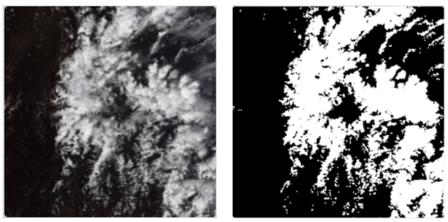


Fig. 10. On left is original image, on right is enhanced and background subtracted image

Subsequently, we proceeded to enhance the dataset images and perform background subtraction to augment the results. This augmentation revealed a notable improvement in the accuracy graph and a reduction in loss after only 2 epochs, as compared to CNN classification without augmentation.

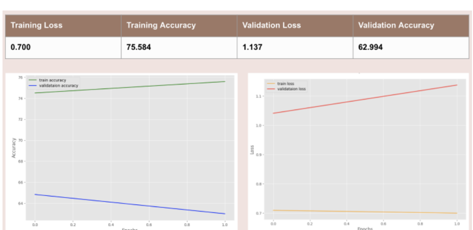


Fig. 11. Before Enhancement and background subtraction 2 Epoch

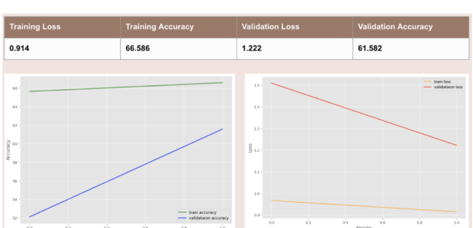


Fig. 12. After Enhancement and background subtraction 2 Epoch

Notably, after 20 epochs, the results became more pronounced, with a slight decrease in training loss by 1.37, a noteworthy increase in training accuracy by 10.326, a reduction in validation loss by 1.106, and a threefold increase in validation accuracy to 25.803.

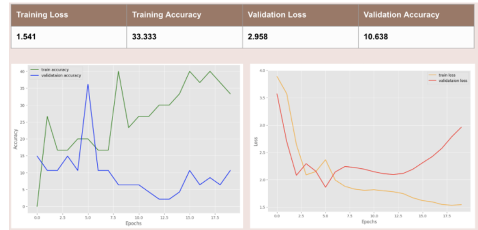


Fig. 13. Before Enhancement and background subtraction 2 Epoch

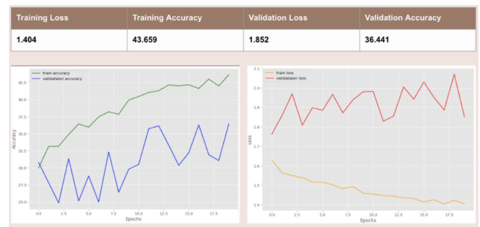


Fig. 14. After Enhancement and background subtraction 2 Epoch

In response to time constraints, we made slight modifications to our approach concerning pixel distribution learning. Currently, we focus on enhancing dataset images and simulating background subtraction to emulate the outcomes of pixel distribution learning background subtraction. Moreover, we intend to explore the tangible benefits of leveraging actual results from pixel distribution learning in future iterations, with a view to enhancing the efficacy of this approach.

VII. Conclusion

Classifying aerosol materials using a convolutional neural network with standard satellite image datasets does not yield satisfactory performance, primarily because the objects are relatively indistinguishable. This assertion is substantiated by the results presented in the aforementioned report, which contrasts training loss, training accuracy, validation loss, and validation accuracy. Nevertheless, enhancing the image and subtracting its background can significantly improve accuracy and mitigate loss, as evidenced by the preliminary results presented in this paper. These findings validate our assumption that CNN classification performs more effectively when comparing patterns of aerosol materials rather than solely relying on the characteristics of regular images.

Enhancement and Background Subtraction	Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
No	2	0.700	75.584	1.137	62.994
Yes	2	0.914	66.586	1.222	61.582
No	20	1.541	33.333	2.958	10.638
Yes	20	1.404	43.659	1.852	36.441

Fig. 15. Result Comparison

REFERENCES

[1] https://natural-resources.canada.ca/climate-change/impacts-adaptations/climate-change-impacts-forests/forest-change-indicators/cost-fire-protection/17783
[2] https://open.alberta.ca/dataset/02352063-5db9-4f25-b4a7-2ada621afd75/resource/0860ecd8-8826-4d72-af5a-8d9860b25511/download/2015wildfirereviewsummarydec2016.pdf
[3] https://ieeexplore.ieee.org/document/8486510
[4] https://complex.ustc.edu.cn/sjwwataset/list.htm
[5] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8307064
[6] https://www.mdpi.com/2072-4292/14/3/536
[7] https://ieeexplore.ieee.org/abstract/document/8892609
[8] https://www.mdpi.com/2079-9292/12/18/3888
[9] https://ieeexplore.ieee.org/document/9293722
[10] https://ieeexplore.ieee.org/iel7/8929048/8932721/08932740.pdf
[11] https://www.sciencedirect.com/science/article/pii/S1569843222002400
[12] https://arxiv.org/abs/2211.00534
[13] https://ieeexplore.ieee.org/document/10150154/
[14] https://www.mdpi.com/2571-6255/6/6/217
[15] https://www.mdpi.com/2072-4292/11/14/1702
[16] https://link.springer.com/chapter/10.1007/978-3-031-22061-6_2
[17] https://www.mdpi.com/2072-4292/15/19/4855
[18] https://www.frontiersin.org/articles/10.3389/fenvs.2022.794028/full
[19] https://www.sciencedirect.com/science/article/abs/pii/S1568494623003800
[20] https://www.sciencedirect.com/science/article/pii/S0165168421003467
[21] https://paperswithcode.com/paper/rapid-deforestation-and-burned-area-detection
[22] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=arnumber=8385121
[23] https://www.sciencedirect.com/science/article/abs/pii/S0925231221003830
[24] https://www.sciencedirect.com/science/article/pii/S0034425721001851
[25] https://www.sciencedirect.com/science/article/abs/pii/S0957417422016499
[26] https://paperswithcode.com/paper/firenet-a-specialized-lightweight-fire-smoke
[27] https://journals.sagepub.com/doi/full/10.1177/1748302619887689#body-ref-bibr9-1748302619887689
[28] https://ieeexplore.ieee.org/document/9368283
[29] https://ieeexplore.ieee.org/document/9888515
[30] https://ieeexplore.ieee.org/document/9633803
[31] https://ieeexplore.ieee.org/document/10083121
[32] https://ieeexplore.ieee.org/document/9716284
[33] https://fireecology.springeropen.com/articles/10.1186/s42408-022-00165-0
[34] https://www.mdpi.com/2079-9292/12/1/228
[35] https://ieeexplore.ieee.org/document/9767911
[36] https://ieeexplore.ieee.org/document/7014233
[37] https://debuggercafe.com/pytorch-imagefolder-for-training-cnn-models/
[38] https://github.com/zhaochenqiu/D_DPDL