Wildfire Smoke Detection System using Deep Learning

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ABSTRACT

This study provides a solution to the problem of detecting wildfire smoke in fire-prone areas. Fire incidents are crucial to the community as they can cause damage to humans and properties. The researcher considers this dilemma to be an example of action detection, and to solve it using deep learning. To create a model in detecting wildfire smokes, this study will utilize the YOLOv3 algorithm which is a great tool in detecting objects in real-time applications. Based on the study's findings, model 30 yielded the highest mAP of 0.9986 (99.86%) and a training loss score of 3.3692. The generated model, Model 30, was applied to the GUI to test and evaluate the performance of the system. The video testing result yielded a 47.64% accuracy, whereas the live feed or webcam yielded an accuracy of 61.55%. Thus, the system is a viable tool in detecting wildfire smoke in real-time application.

Keywords: *object detection, deep learning, wildfire smoke, yolov3*

INTRODUCTION

Wildfire smoke is a vast threat to damaging the human, properties, and wildlife ecosystem (Rahman Et. Al., 2021). Every year, thousands of lives and billions worth of property damage are lost due to the seemingly inescapable fires which are often caused by negligence and sheer apathy of its consequences (IFSEC, 2021). Analysis shows that fire suppression efforts have been effective to stop most fires by a successful initial attack. The probability of a successful initial attack and avoiding wildfires decreases exponentially with every minute that passes after ignition. As the danger increases, the demands and requirements also increase in detecting a starting fire as quickly as possible after the ignition and analyzing the precise location of the fire (Dreibach, 2017) , On the other hand, wildfire smoke can also harm humans in multiple ways. The smoke it emits can cause difficulty in breathing, can irritate the eyes, or worsen, can cause immediate health effects (CDC 2013). A device or a system would be a necessary solution to have early detection of the wildfire smokes. Not only it can reduce its threats to properties and the environment, but it can also reduce the health effects that it will cause to humans.

The detection system for wildfire smokes is not entirely a new idea. There are already few existing studies about smoke detection. Traditional methods of wildfire detection, which are mainly based on human observation from watchtowers, are inefficient. The inefficiency is primarily due to the spatiotemporal connection. Rahman et.al., (2021), presents a new methodology based on texture and color for the detection and monitoring of different sources of forest fire smoke using unmanned aerial vehicles (UAVs). Genevose et. al., (2011). designed low-power and low-cost platforms for smoke detection. The approach takes into account bad quality frame sequences and employs computational intelligence techniques, in particular describing the adoption of neural networks. The approach performed well even in the presence of non-ideal conditions. Conditions of poor visibility can cause missed detections but do not raise the number of false alarms.

Since the long-distance wildfire smoke usually moves slowly and lacks salient features in the video, the detection is still a challenging problem. Thus, a novel video-based method for long-distance wildfire smoke detection is proposed in the study of Zhou et al. The Maximally Stable Extremal Region (MSER) detection method was used to extract local extremal regions of the smoke. This makes the initial segmentation of possible smoke regions less dependent on the motion and color information. Results showed that the proposed method can reliably detect long-distance wildfire smoke and simultaneously produce very few false alarms in actual applications. The features of smoke are changeable and disturbances such as haze, sky, and change of lightness can also be captured by the motion detection algorithm. All of them increase the false positive rate significantly.

Dark channel prior and multi-threshold segmentation are used (Qin et.al, 2019) to remove the disturbances such as a white house, haze, and sky before detection. After motion object segmentation, the regions which are moving but not blocked are activated. Finally, features of motion cells are extracted and a support vector machine is used to classify the motion cells. Remote sensing using computer vision techniques can provide early detection from a large field of view along with providing additional information such as the location and severity of the fire. This paper (Shakhadri, 2021) adds to the existing research by proposing a novel method of detecting forest fire using color and multi-color space local binary pattern of both flame and smoke signatures and a single artificial neural network. The training and evaluation images have been mostly obtained from aerial platforms with challenging circumstances achieving F1 scores of 0.84 for flame and 0.90 for a smoke with a processing speed of 19 fps outperforming SVM, Random Forest, and Bayesian classifiers.

Developing an accurate wildfire smoke system is challenging some factors that should be considered like illumination and distance. Therefore, the approach proposed in this paper attempts to solve this problem by using a Convolutional Neural Network (CNN) that can detect wildfire smoke in real-time even under certain conditions like distance from the camera and/or illumination. This study aims to propose a real-time wildfire smoke detection system using the YOLOv3 algorithm. In the study of Redmon et.al, (2018) it is proved that YOLO is an algorithm known for its high accuracy and ability to detect objects running in real-time.

This study aims to develop a real-time wildfire smoke detection system using the YOLOv3 algorithm. YOLO is an algorithm known for its high accuracy, ability to detect objects running in real-time, and it has minimal computing complexity.

This study will be significant in easily detecting wildfire smoke in the community especially the fire-prone areas. This will also be beneficial to the fire protection agency units to help them locate the precise location of the fire incident. This study mainly focuses on detecting the wildfire smoke and not the wildfire. Furthermore, this study will not guarantee to prevent fire incidents or any cause of wildfires, instead, it is only geared to detect the location of the wildfire smoke so then responders could easily deploy rescue operations when an accident occurs.

METHODOLOGY

In this section, the architecture of the YOLOv3 algorithm will be explained, the technique for detecting wildfire smoke, model training, and testing using a custom data set.

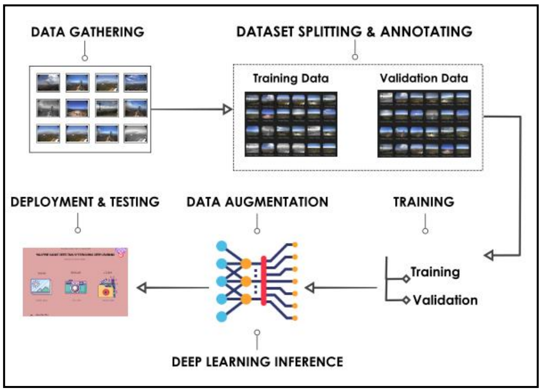

Figure 1. Diagram of the system workflow design.

Figure 1 depicts the system workflow design diagram. The system's development or design went through several steps or stages, including dataset preparation or data gathering, data splitting, data annotating, model training and evaluation, and finally, model inferencing.

Preparing and Collection of Dataset

The dataset utilized in this study was from Roboflow and was released by AI for Mankind in collaboration with HPWREN under a Creative Commons by Attribution Non-Commercial Share Alike license. The dataset consists of 737 raw images. Figure 2 shows the sample images of the dataset for the wildfire smoke. The dataset was divided into two sets, the training, and validation sets. The training dataset comprised 80% while the validation dataset consist only 20%.

Figure 2. Sample Datasets for wildfire smoke.

Dataset Annotation

To annotate and label the datasets, the researcher utilized LabelImg. In annotating the datasets for both the training and validation image datasets, a rectangular bounding box was built in the body form region of wildfire smoke. The result is an XML file containing the annotated pictures' coordinates in PascalVOC format.

File Edit Format View Help
```
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\image (1).jpg</path>
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	</object>
</annotation>
```


Figure 3. Dataset annotations of wildfire smoke images.

Shown in Figure 3 is an image of the wildfire smoke with its annotation. On the left part is the annotated image that has a rectangular red bounding box on the region of wildfire smoke. While on the right part is the XML file containing the coordinates of the region with a bounding box.

Deep Learning Algorithm

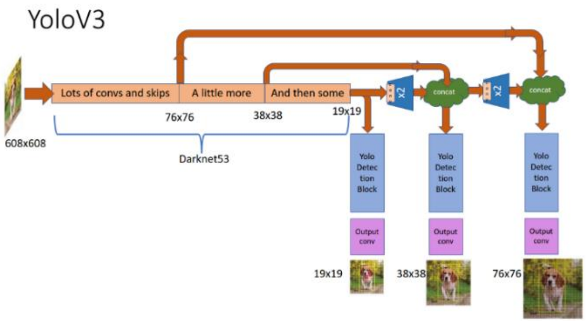

Figure 4. YOLOv3 Architecture

YOLOv3 or You Only Look Once [10] is an object detector proposed by Joseph et al., that takes the detection procedure as a regression task. This method increases the speed of detection and accepts input pictures of different sizes [14]. YOLOv3 uses multi-scale prediction, which means it is detected on multiple-scale feature maps. YOLOv3 can achieve real-time detection on the high-performance computer utilizing the powerful computing capability of the GPU. Because the performance of embedded devices is far less than that of high-Performance computers, it is often impossible to achieve real-time applications.

Model Evaluation

To ensure that the best-trained model was chosen for model inference detection, the mAP (mean Average Precision) was utilized to compare all the trained models. It will create files (h5 file) that will be used in the testing procedure. The model's detection accuracy improves as the mAP increases, the mAP is AP's average (mean average precision).

Average Precision (AP): Interpolate the accuracy at consecutive recall phases until the AP (1) is determined to reduce the effect of the curve wiggles. The area under the interpolated curve is defined as AP, which can be calculated using the method below. The interpolated precision ρ_{interp} (2) defines a given degree of recall r as the maximum level of accuracy discovered at any stage of recall r'≥r.

$$AP = \sum_{i-1}^{n-1}(r_{i+1} - r_i)\rho_{interp}(r_i + 1) \quad (1)$$

$$\rho_{interp}(r_i + 1) = max\ \rho(r') \quad (2)$$

Mean Average Precision (mAP): The average precision (AP) across all tests is called mean average precision (mAP) (3), where 0 is the number of queries in the set and AP i is the average precision (AP) for a specific query, o.

$$mAP = \frac{\sum_{i=1}^{0} AP_i}{0} \qquad (3)$$

Model Inferencing and Testing

To deploy the detection model, the researcher develops a graphical user interface (GUI) utilizing the Anaconda IDE, PyQt5, and ImageAI detection library. The GUI consists of three essential functions: (1) single image detection, (2) video detection, and (3) live feed detection. To have an inference, of the model, the deep learning model h5 file with the highest mAP and its accompanying JSON configuration file were utilized.

To test the model, the researcher used other images and video files of wildfire smoke that are not part of the dataset. Using images that are not included in the 300 photos used for training and validation will prevent any biases in the testing accuracy (4) findings.

$$Accuracy = \frac{No.of\ Detected\ Object}{Total\ No.of\ Detected\ Objects} \times 100 \qquad (4)$$

RESULTS AND DISCUSSION

This section will discuss the training, validation, and testing findings.

Training and Validation Results

Figure 5 depicts the training and validation results of the YOLOv3 model. The experimental training level is set at 34. The researcher trained the model with a total of 97 training levels. However, some trained models are missing, which is why the researcher decided to not include them in the graph. Thus, only 34 epochs or training levels are shown in Figure 5.

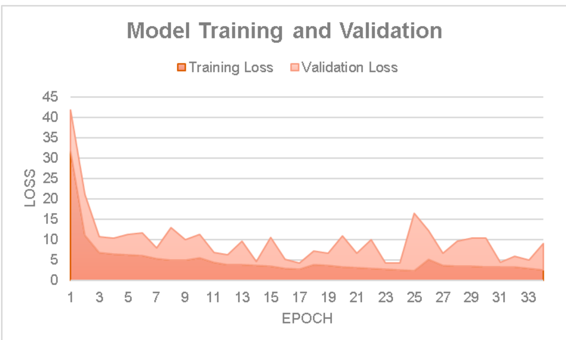

Figure 5. YOLOv3 training and validation results.

As seen in Figure 5, the training loss was represented by the red region, while the validation loss was represented by the pink region.

On the initial training, the model has a training loss of 31.95% and a 9.94% validation loss. And on the final training, it has a training loss of 2.62% and a validation loss of 6.5104%. As may be observed in Figure 5, the training and validation loss score for epoch 1 was the highest, whereas the training and validation loss score for epoch 33 was the lowest. Another observation from Figure 5 is that the loss scores for both training and validation of each level have different peaks and variations. Because of the different batches in the training of epoch, the loss scores also vary.

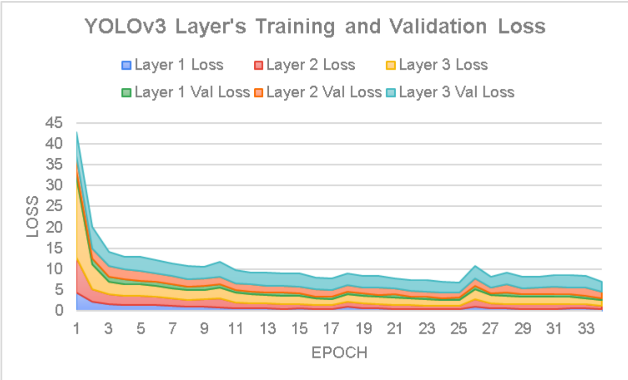

Figure 6. YOLOv3 layer’s training and validation loss

Figure 6 depicts the YOLOv3 layer’s training and validation losses. As may be observed, the training length increases while the loss score decreases. Considering that it goes through a training process, the yolov3 model also learns from the provided dataset which significantly diminishes the loss score. On the other hand, the val loss is a variable that tends to decrease over time. A validation set was designed to test a single model, but it may also be used to test several models.

Evaluation of Model

The precision of the dataset validation is represented by the mAP number, which is expressed as a percentage. The validity number is close to its greatest attainable value since the mAP is equivalent to 1 (100 %). The mAP obtained during the model evaluation is shown in Fig. 7. In this graph, with an mAP of 0.5053, Model 14 has the lowest performance. However, the other model’s performance shows an unsteady improvement of accuracy. Even though Model 1 has the highest loss score, Model 14 has the lowest mAP. It can be observed that having a low loss score does not guarantee a higher result of mAP.

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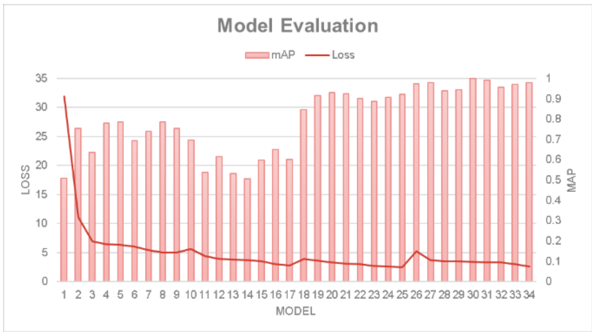

Figure 7. Evaluation of models.

Among the models shown in Fig. 7, Model 30 produced the greatest results having an mAP value of 0.9986 (99.86%) and an equal training loss of 3.3692. Therefore, model 30 will be employed in the inferencing and testing process.

Inference and Testing of Model

Fig. 8 depicts the GUI of the wildfire smoke detection system. The generated model 30 was applied to each frame obtained by the capturing instrument. Thus, the GUI will be deployed to evaluate the performance of the system and the inference of model 30.

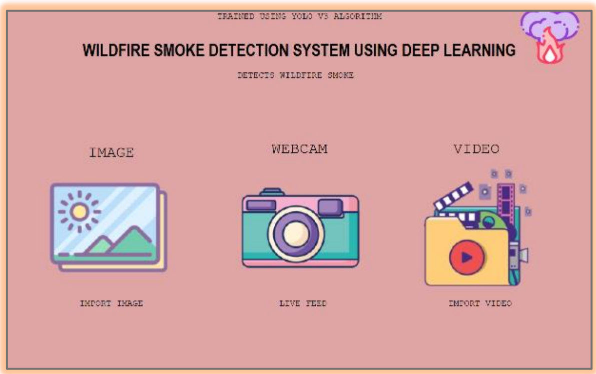

Figure 8. Model inference's GUI

As shown in Fig. 8, there are three options to test and evaluate the performance of the system: (1) import image, (2) live feed or through webcam, and (3) import video.

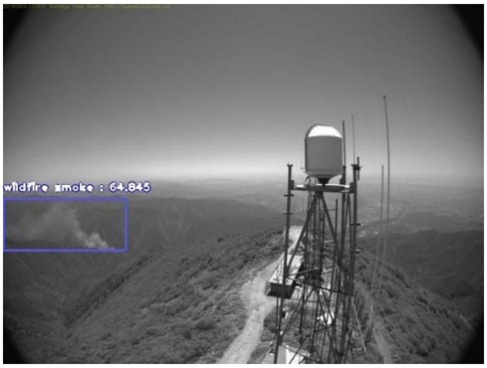

Figure 9. Single Image Testing

Figure 10. Live Feed testing

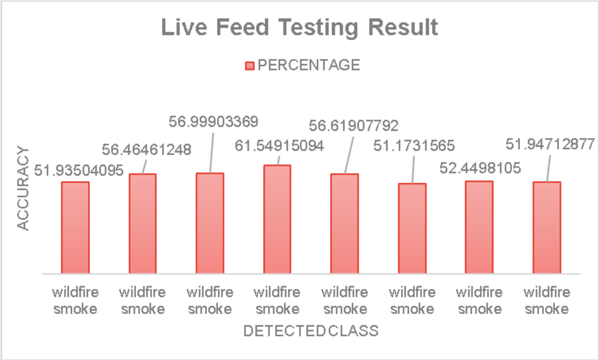

Figure 11. Live Feed testing result.

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Figure 12. Video Testing

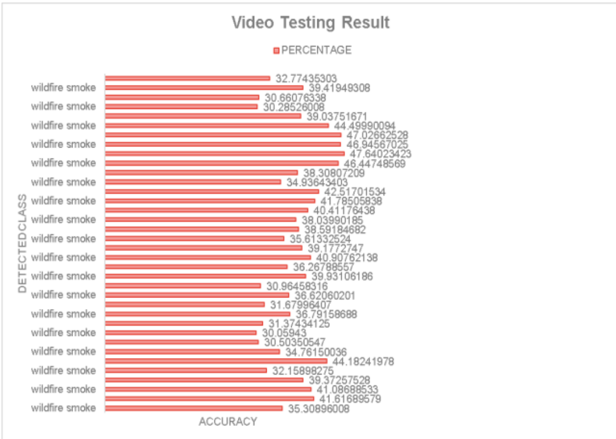

Figure 13. Video Testing Result

Table I
Comparison of Various Wildfire Smoke Detection Algorithms

METHOD	DATA	mAP
Caffe Model	Custom	97.57%
SuperDuper-V1 [12]	AI for Mankind	75.06%
SuperDuper-V2 [12]	AI for Mankind	86.69%
SuperDuper-Edge [12]	AI for Mankind	68.22%
YOLOv3 (Ours)	AI for Mankind	99.86%

Table 1 shows the comparison of various wildfire smoke detection algorithms. The SuperDuper-V1, SuperDuper-V2, and SuperDuper-Edge models were developed by AI for Mankind. It can be observed that the researcher's YOLOv3 model achieved the highest mAP compared to the other algorithms. Thus, it can be concluded that this study beats the earlier algorithms for identifying wildfire smoke by a significant margin when custom datasets were employed.

CONCLUSION

Wildfire smoke happens when wildfire occurs. This wildfire smoke can damage the human system when inhaled. There is a need for a system that can accurately detect wildfire smoke and can help the fire responders to easily find the location where the fire incident takes place. The system utilizes the YOLOv3 algorithm, which uses CNN to implement the deep learning technique. Based on the research finding's, Model 30 accumulate the highest mAP of 0.9986 (99.86%), thus will be utilized as the model inference in deploying the system. A GUI was developed wherein there were three options to test the performance of the system: import image, import video, and live feed. On the single image testing, the system achieved an accuracy of 64.845. On the video testing, the system achieved the highest accuracy of 47.64. And lastly, on the live feed testing, the system achieved the highest accuracy of 61.55. In conclusion, although the accuracy scores are quite low, the study is still a reliable tool in detecting wildfire smoke accurately.

RECOMMENDATIONS

The researcher suggests that instead of only using this dataset of wildfire smoke from AI for Mankind, look for other images of a wildfire smoke with better quality to easily achieve a higher mAP score in the first 25 epoch training.

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