
Scrapping The Web For Early Wildfire Detection

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Abstract

Early wildfire detection is of the utmost importance to enable rapid response efforts, and thus minimize the negative impacts of wildfire spreads. To this end, we present PYRONEAR₂₀₂₃, a web-scraping-based dataset composed of videos of wildfires from a network of cameras that were enhanced with manual bounding-box-level annotations. Our dataset was filtered based on a strategy to improve the quality and diversity of the data, reducing the final data to a set of 10,000 images. We ran experiments using a state-of-the-art object detection model and found out that the proposed dataset is challenging and its use in concordance with other public dataset helps to reach higher results overall. We will make our code and data publicly available.

1 Introduction and Related Work

Wildfires have become an increasingly prevalent and devastating natural disaster worldwide, causing loss of life, destruction of property, and significant environmental damage. While wildfires have always been a part of nature’s cycle, human activities and climate change have exacerbated their frequency and intensity. As such, there is an urgent need to develop and implement advanced technologies to prevent wildfires, as well as predicting their behavior.

Given the undeniable link between climate change and the increasing frequency of wildfires, the urgency of addressing this issue is underlined by projections from the Intergovernmental Panel on Climate Change (IPCC), which anticipate a continued rise in the occurrence of extreme events like wildfires.² The urgency of responding to this crisis is augmented by its ramifications for sustainable development, the environment, and social equity.

Early wildfire detection is of paramount importance in mitigating the catastrophic consequences of these increasingly prevalent natural disasters, driven by climate change-induced warmer temperatures and drier conditions Reidmiller et al. [2018]. Recent advancements in artificial intelligence (AI) and deep learning (DL) techniques have spurred innovative methodologies for addressing this critical issue, yielding a profusion of methods and datasets tailored to diverse aspects of early wildfire detection.

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²https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_LongerReport.pdf

Fernandes et al. [2023] demonstrated the use of EfficientDet for automatic early detection of wildfire smoke with visible-light cameras, emphasizing the significance of large and representative datasets for training. Their dataset consists of 14,125 smoke and 21,203 non-smoke images. Their results achieved a true detection rate of 80.4% and a false-positive rate of 1.13%, outperforming previous studies focusing on smoke plumes. Yazdi et al. [2022] introduced Nemo, an open-source benchmark for fine-grained wildfire smoke detection, tailored to the early incipient stage. They adapted Facebook's DEtection TRansformer (DETR) Carion et al. [2020] to wildfire detection, achieving superior performance in detecting smoke across different object sizes. Their model detected 97.9% of fires in the incipient stage, outperforming baseline methods. Dewangan et al. [2022] propose a model with an associated dataset: SmokeyNet and Fire Ignition Library (FigLib). The dataset is publicly available and composed of 25,000 labeled wildfire smoke images as seen from fixed-view cameras deployed in Southern California. The proposed model relies on a novel deep learning architecture using spatiotemporal information from camera imagery for real-time wildfire smoke detection, which outperformed comparable baselines and even rivaled human performance, demonstrating the potential for real-time wildfire smoke detection.

Resource-efficient solutions have been explored to extend the applicability of wildfire detection systems. de Venâncio et al. [2022] proposed an automatic fire detection system based on deep CNNs suitable for low-power, resource-constrained devices, achieving significant reductions in computational cost and memory consumption while maintaining performance. In the same vein, Khan and Khan [2022] presented "FFireNet," a deep learning-based forest fire classification method, utilising a small neural network, the MobileNetV2 model for feature extraction and achieving remarkable accuracy in binary classification of fire images.

Satellite imagery has been a pivotal data source for early wildfire detection. Barmpoutis et al. [2020] offered an overview of optical remote sensing technologies used in early fire warning systems. They conducted an extensive survey on flame and smoke detection algorithms employed by various systems, including terrestrial, airborne, and spaceborne-based systems. This review contributes to future research projects for the development of early warning fire systems. James et al. [2023] developed an efficient wildfire detection system utilizing satellite imagery and optimized convolutional neural networks (CNNs) for resource-constrained devices, using a MobileNet on an Arduino Nano 33 BLE.

Video-based fire detection techniques have emerged as a promising avenue for early wildfire detection. Jin et al. [2023] provided a comprehensive review of deep learning-based video fire detection methods, summarizing recent advances in fire recognition, fire object detection, and fire segmentation using deep learning approaches. Their review provided insights into the development prospects of video-based wildfire detection.

de Venâncio et al. [2023] proposed a hybrid method for fire detection based on spatial and temporal patterns, combining CNN-based visual pattern analysis with temporal dynamics to reduce false positives in fire detection. Additionally, Marjani and Mesgari [2023] introduced "FirePred," a hybrid multi-temporal CNN model for wildfire spread prediction, emphasizing the importance of considering varying temporal resolutions in fire prediction models.

These systems have been applied to support wildfire management decisions. Bot and Borges [2022] conducted a systematic review of applications of machine learning techniques for wildfire management decision support. Their emphasis was on summarizing applications across different case studies, machine learning methods, case study locations, and performance metrics, highlighting the potential of machine learning in enhancing fire management decision support.

Concerning the datasets, at first view many of them can be found in the literature with a focus on wildfire detection. Nevertheless works such as Toulouse et al. [2017], Sharma et al. [2017], Foggia et al. [2015] are actually fire detection datasets, containing pictures of fires at an already advance stage. In this work, as we mainly focus on smoke plumes in order to detect early wildfires from watchtowers, we discard the (easier) task of fire detection. In this context, it is notable to remark that only a very few of the datasets containing annotations for the smoke plume detection are publicly available.

In general, there are two main sources of videos for smoke plumes detection in the wild that are available online: HPWREN [2023] (High Performance Wireless Research & Education Network) and ALERTWildfire [2023]. These two sources were used to create several datasets. Leveraging the camera network of the HPWREN, [Dewangan et al., 2022, Govil et al., 2020, AIforMankind, 2023]

propose annotated datasets for early wildfire detection, while other works [Schaetzen et al., 2020, Yazdi et al., 2022, AIforMankind, 2023] propose datasets obtained from the ALERTWildfire network. Finally, from private sources and not publicly available, Fernandes et al. [2022] constructed a dataset of 35k images from Portugal that are annotated in smoke plumes. It is composed of 14,125 images that contain smoke plumes and 21,203 that do not.

2 Datasets Collection, Fusion And Annotation

2.1 Available Datasets

In the development of an early wildfire detection model, the assembly of a comprehensive and diverse dataset is crucial. Given the limited number of Pyronear cameras currently deployed in the field, our effort to gather data extends to additional sources. This subsection outlines the primary sources of data and the derivative datasets that have been instrumental in our research.

Primary Data Sources Our data acquisition strategy leverages two main sources:

- **HPWREN:** Funded by the National Science Foundation, HPWREN is a non-commercial, high-performance, wide-area, wireless network of Pan-Tilt-Zoom (PTZ) cameras serving Southern California. It focuses on network research, including the demonstration and evaluation of its capabilities in wildfire detection.
- **ALERTWildfire:** A consortium of universities in the western United States provides access to advanced PTZ fire cameras and tools, aiding firefighters and first responders in wildfire management, covering extensive regions spanning Washington, Oregon, Idaho, California, and Nevada. The ALERTWildfire website³ grants public access to live feeds from these cameras.

Derived Datasets From these sources, several projects have proposed datasets that are of interest to our wildfire detection initiative:

- **SmokeFrames:** Developed by Schaetzen et al. [2020] this dataset comprises nearly 50k images sourced from ALERTWildfire. To tailor it to our specific requirements, we created a subset, *SmokeFrames-2.4k*, consisting of 2410 images from 677 different sequences, with an average of 3.6 images per sequence. This subset includes a significant number of false positives, essential for a comprehensive wildfire detection model.
- **Nemo:** The dataset of Yazdi et al. [2022] includes frames extracted from raw videos of fires captured by ALERTWildfire’s PTZ cameras, encompassing various stages of fire and smoke development.
- **Fuego:** Initiated by the Fuego project [Govil et al., 2020], this dataset was created by manually selecting and annotating images from the HPWREN camera network, based on historical fire records from Cal Fire. The authors are claiming 8500 annotated images with a focus on the early phases of fires, but only a subset of 1661 images are publicly available.
- **AiForMankind:** Two training datasets emerged from hackathons organized by AI For Mankind [AIforMankind, 2023], a nonprofit focusing on using AI for social good. These datasets, combined into one, offer a substantial collection of annotated images for smoke detection and segmentation.
- **FIGLib:** Dewangan et al. [2022] propose the Fire Ignition image Library (FIGLib) which was composed of 24,800 images from South California from 315 different fires. It is the official dataset from the HPWREN.

2.2 Creation of the PYRONEAR₂₀₂₃ Dataset

This section presents the collection of the data, its annotation using a homemade platform and a summary of the final dataset.

³<https://www.alertwildfire.org/>

2.2.1 Data Acquisition Strategy

Our wildfire detection initiative utilizes the AlertWildfire camera network, which comprises approximately 130 cameras. It’s crucial to note that the actual number of operational cameras fluctuates due to occasional unavailability, the reasons for which are often unclear. Despite these variances, we ensure comprehensive monitoring.

The core of our data collection is an automated scraping script that interacts with the AlertWildfire API. This script retrieves images from each camera at the predetermined frequency of one image per minute, set by AlertWildfire. While we would prefer a higher frequency—since our cameras can capture an image every 30 seconds for analysis—this limitation necessitates that we work with around 1,440 images per camera per day, summing up to about 187,200 images daily across the network.

Our initial filtering stage targets the elimination of nighttime images, as our current model is designed primarily for daylight image analysis. Nighttime images are in grayscale due to the cameras switching to infrared mode, and these are automatically excluded from our dataset.

After filtering out the nighttime images, we perform inference on the remaining daylight images using our model. This model analyze each image, and any with a wildfire detection score above 0.2 is marked as a potential fire event. To ensure comprehensive coverage of potential fire events, we also save images taken 15 minutes before and after each detected event from the same camera. This approach helps in capturing a broader timeline around each potential wildfire incident.

All the images flagged during this process, including both potential wildfire detections and corresponding time-framed images, are stored for later annotation. This rich collection, encompassing potential early signs of wildfires as well as false positives, offers a diverse dataset. This dataset is invaluable for enhancing the performance and accuracy of our wildfire detection models, particularly in distinguishing true wildfires from non-threatening natural occurrences.

In this way, because the fires all grow to a point where they are easily detectable, we capture all of the events. This collection methods, which is already based on a trained model, helps to gather a diverse range of images, from clear instances of wildfires to challenging scenarios that have historically led to a false detection.

2.2.2 Collaborative Annotation Platform

In order to annotate the wildfire data scrapped from the web, we developed a collaborative annotation tool with custom code in order to streamline the annotation process. We collected a total of 120,000 annotations in a few month by leveraging the help of the PyroNear community. It had to answer to a few constraint, especially the one that as the annotators were all volunteers using their free time to help developing an open-source dataset and model. We gave to the volunteers a precise quantity of images, which number was selected as 150 so that the annotation task would take less than 15 minutes so that it can be done during a train commute or a break between two activities, and it kept the cognitive load low in order to avoid mistakes and care the annotators. Finally, the platform have also been designed to ensure a smooth and coherent workflow. A snapshot of the platform is visible in Figure 1.

Each of the images has been annotated by five annotators in order to minimize the label errors. To validate the quality of the annotationo, we calculated the inter-annotator agreement using Krippendorff’s α Krippendorff [2013] with the presence or not of fire in each image, and obtained satisfying value.

2.2.3 Final Dataset: PYRONEAR₂₀₂₃

The creation of the PYRONEAR₂₀₂₃ dataset is a carefully orchestrated process, tailored to suit our current focus on one-image object detection. Initially, we started with an extensive collection of 120,000 labeled images. With a 5-times cross-labeling approach, this pool was refined down to 24,000 unique images.

Given our emphasis on one-image object detection, it was crucial to streamline the dataset to reduce redundancy and enhance model performance. Our reduction process involved two critical steps:

Selective Removal of Background Images: To maintain a balanced dataset, we strategically reduced the number of background images. This step ensured that our dataset did not disproportionately favor

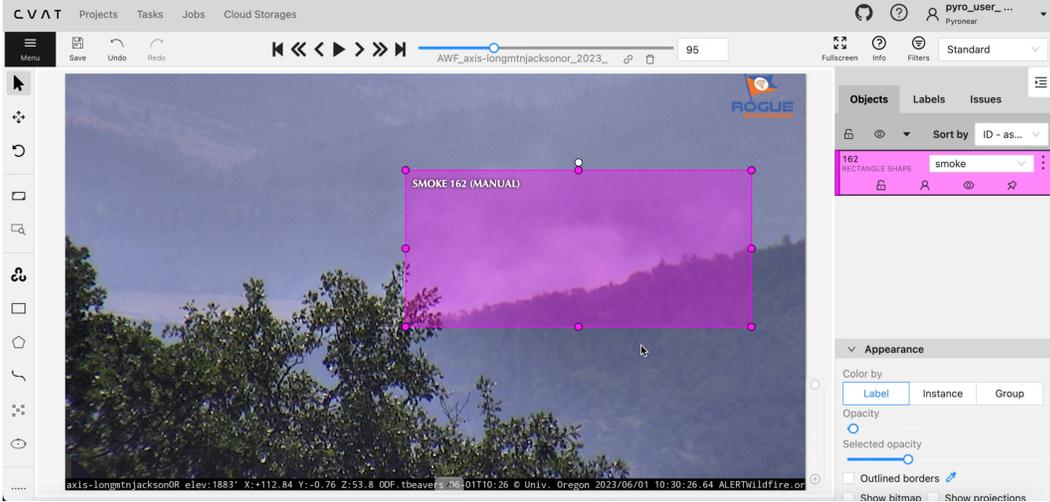


Figure 1: Snapshot of the Computer Vision Annotation Platform for Smoke Plume Detection.

non-wildfire scenarios. We aimed to keep around 15% of background images to achieve a balanced representation. After this filtering, the dataset was condensed to roughly 10,000 images.

Subsampling to Eliminate Redundancy: Acknowledging the potential for redundancy, especially in images sourced from video sequences, we implemented a subsampling strategy. By retaining only one image every 10 minutes, we effectively minimized repetitive or near-identical images. This approach was crucial in preserving the diversity of the dataset while ensuring its relevancy to our one-image object detection focus. The dataset was thus further refined to 1,096 images, including 951 smoke images.

The final composition of the PYRONEAR₂₀₂₃ dataset is:

Training Set: 987 images, including 836 smoke images. **Validation Set:** 109 images, with 88 smoke images. While the current version of the PYRONEAR₂₀₂₃ dataset is optimized for one-image object detection, our future plans include the utilization of the entire collection of images. We intend to develop a temporal model that leverages a series of images for prediction, thus enhancing the accuracy and robustness of wildfire detection.

3 Experiments and Results

In this study, our primary objective is to evaluate the quality of various datasets by conducting a preliminary optimization process.

3.1 Methodology

We use the YOLOv8 model [MMYOLO, 2023], renowned for its proficiency in diverse detection scenarios. For frugality reasons because of the type of our task, the small version of the model was chosen for its balance between speed, size and accuracy. The optimal batch size and number of epochs were found using a grid search in $\{50, 100\}$ and $\{2^k, k = 4..6\}$.

Dataset Splitting Strategy In preparing our datasets for the model training and validation process, we were guided by the existing split in the Nemo dataset, where approximately 9.3% of the data was allocated for validation. To maintain consistency across all datasets and ensure a comparable evaluation framework, we adopted a similar approach for the other datasets, targeting a close approximation of a 10% split for the validation set. This strategy enables a balanced and uniform methodology for assessing the performance of our models across different datasets, ensuring that each dataset is represented fairly in both training and validation phases.

Dataset	Total Images	Wildfire Images	Train*	Validation*
AiForMankind	2935	2584	2642 / 2305	293 / 279
Fuego	1661	1572	1495 / 1421	166 / 151
Nemo	2691	2570	2440 / 2333	251 / 237
SmokeFrames-2.4k	2410	976	2169 / 906	241 / 70

Table 1: Summary of Datasets: Total and Wildfire Images in Training and Validation Sets. In the columns with * are shown Total/Wildfire images.

Metrics Following past works [Schaetzen et al., 2020, Yazdi et al., 2022, Dewangan et al., 2022] we use precision, recall, and the F1 score as metrics in order to validate the different models. We chose not to use the usual object detection metric such as mean average precision (mAP) as the goal is about correctly classifying areas in an image as indicating a wildfire or not, without being able to get the contours of the smoke plumes which can be subjective.

4 Results

4.1 Single Dataset Evaluation

Dataset	Best Model	Highest F1 Score	Confidence	Batch Size	Epochs
SmokeFrames	SmokeFrames3	0.920	0.15	32	50
Nemo	Nemo3	0.899	0.02	64	100
AiForMankind	Aiformankind2	0.883	0.03	32	50
PYRONEAR ₂₀₂₃	Wildfire3	0.793	0.04	16	100
Fuego	Fuego	0.623	0.02	32	100

Table 2: Best Performing Model for Each Dataset Sorted by Highest F1 Score with Corresponding Confidence Threshold, Batch Size, and Epochs. Best models depends on the hyperparameters.

4.2 Cross-Dataset Model Evaluation

Having trained several models on each of our diverse datasets, the next critical phase of our study involves a rigorous cross-dataset evaluation. This process is pivotal in determining not only the versatility and robustness of our models but also their applicability in a wide range of real-world scenarios.

4.3 Selection of Optimal Models and Confidence Thresholds

Our approach begins with the careful selection of the best-performing model from each dataset. The criterion for this selection is based on a F1 score, ensuring that each chosen model demonstrates the highest level of accuracy and reliability within its training domain. Alongside this, we also identify the optimal confidence threshold. The performances of the model trained on a combined dataset on the different test sets are shown in Table 4.

5 Future Enhancements: Towards PYRONEAR₂₀₂₄

While the cross-labeling approach used for PYRONEAR₂₀₂₃ has significantly contributed to the accuracy of our dataset, it has also led to a substantial reduction in the number of images we could include. Acknowledging this limitation, we are currently developing a new methodology for the upcoming PYRONEAR₂₀₂₄ dataset, which aims to semi-annotation process.

Faster Annotation We are exploring semi-automatic annotation techniques that will accelerate the labeling process while maintaining high-quality annotations. By integrating advanced algorithms with manual oversight, we can swiftly annotate large volumes of images without compromising on accuracy.

Train Dataset	Test Dataset	Precision	Recall	F1 Score
PYRONEAR ₂₀₂₃	AiForMankind	0.4493	0.2222	0.2974
	Fuego	0.3750	0.0397	0.0719
	Nemo	0.7386	0.7236	0.7310
	SmokeFrames-2.4k	0.3056	0.9167	0.4583
	PYRONEAR ₂₀₂₃	0.7604	0.8295	0.7935
Nemo	AiForMankind	0.9402	0.6201	0.7473
	Fuego	0.3889	0.2781	0.3243
	Nemo	0.8528	0.9496	0.8986
	SmokeFrames-2.4k	0.3503	0.9718	0.5149
	PYRONEAR ₂₀₂₃	0.6364	0.6292	0.6328
AiForMankind	AiForMankind	0.9186	0.8495	0.8827
	Fuego	0.7647	0.7697	0.7672
	Nemo	0.7812	0.3151	0.4491
	SmokeFrames-2.4k	0.4356	0.6111	0.5087
	PYRONEAR ₂₀₂₃	0.7937	0.5682	0.6623
SmokeFrames	AiForMankind	0.9750	0.4194	0.5865
	Fuego	0.5000	0.0066	0.0131
	Nemo	0.8737	0.7004	0.7775
	SmokeFrames-2.4k	0.9545	0.8873	0.9197
	PYRONEAR ₂₀₂₃	0.5217	0.1364	0.2162
Fuego	AiForMankind	0.6370	0.6307	0.6338
	Fuego	0.8352	0.4967	0.6230
	Nemo	0.4719	0.1743	0.2545
	SmokeFrames-2.4k	0.2833	0.2329	0.2556
	PYRONEAR ₂₀₂₃	0.4762	0.1136	0.1835

Table 3: Performance of the best models across different datasets

Tested Dataset	Precision	Recall	F1 Score
AiForMankind	0.9565	0.9462	0.9514
Fuego	0.9083	0.7171	0.8015
Nemo	0.8750	0.9156	0.8948
SmokeFrames-2.4k	0.6106	0.9718	0.7500
PYRONEAR ₂₀₂₃	0.7660	0.8182	0.7912
Combine	0.8590	0.8839	0.8713

Table 4: Performance of the 'Combine3' Model Across Different Datasets at Confidence Threshold 0.05

Normalization of Annotations The semi-automatic approach also aims to standardize the annotation process across different users. This consistency is crucial for ensuring that the dataset reflects a uniform understanding of wildfire and smoke characteristics.

Reduced Cross-Labeling With the improved efficiency and consistency brought by semi-automatic annotation, we anticipate the need for cross-labeling to decrease significantly. This reduction will enable us to retain a larger portion of the images initially collected, thereby enriching the PYRONEAR₂₀₂₄ dataset with a broader range of data.

These advancements are expected to not only enhance the volume of annotated data but also to improve the overall quality and representativeness of the PYRONEAR₂₀₂₄ dataset. This progression illustrates our commitment to continuously refining our methodologies in response to the evolving challenges of wildfire detection and monitoring.

6 Conclusion

In this paper we presented PYRONEAR₂₀₂₃, a new dataset for smoke plume detection. We collected it by scrapping online data and an already trained model in order to get the most challenging examples. We kept the images before and after every fire event in order to make it usable by sequential models taking into account the temporality. The dataset was then re-annotated by a pool of volunteers using an online platform designed for the purpose. We showed that training using our dataset helps to improve smoke plume detection models in other public datasets. This data collection and annotation effort will be pursued in order to extend this dataset to other domains, such as new landscape and meteorological conditions, and it will be online soon for research and non-profit purposes.

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7 Supplementary Material

7.1 Results with the different hyperparameters

Following our comprehensive grid search and optimization process, we present the detailed results for each dataset in Tables 5 to 10. These tables encapsulate the outcomes of our hyperparameter tuning, showcasing the optimal settings that yielded the highest F1 scores for each dataset. The results are indicative of each dataset’s unique characteristics and the efficacy of the YOLOv8s model under varying training conditions.

In addition to the tabular data, we also provide F1 score curves for each dataset, corresponding to the tables. These curves, shown below each table, visually represent the performance of the models across different confidence thresholds. The inclusion of F1 curves offers an intuitive understanding of the model’s classification performance, highlighting the trade-offs between precision and recall at various thresholds. This graphical representation complements the tabulated results, providing a more holistic view of the model’s capabilities in detecting potential wildfire indicators within each dataset.

Model	Threshold	F1 Score	Recall	Precision	Batch Size	Epochs
Wildfire3	0.04	0.793	0.830	0.760	16	100
Wildfire4	0.03	0.771	0.784	0.758	16	50
Wildfire	0.08	0.764	0.682	0.870	64	50
Wildfire6	0.03	0.747	0.705	0.795	64	50
Wildfire2	0.09	0.759	0.682	0.857	32	50
Wildfire5	0.18	0.726	0.602	0.914	64	100

Table 5: Optimal Thresholds and Corresponding F1 Scores, Recall, and Precision for Wildfire Models, Sorted by F1 Score

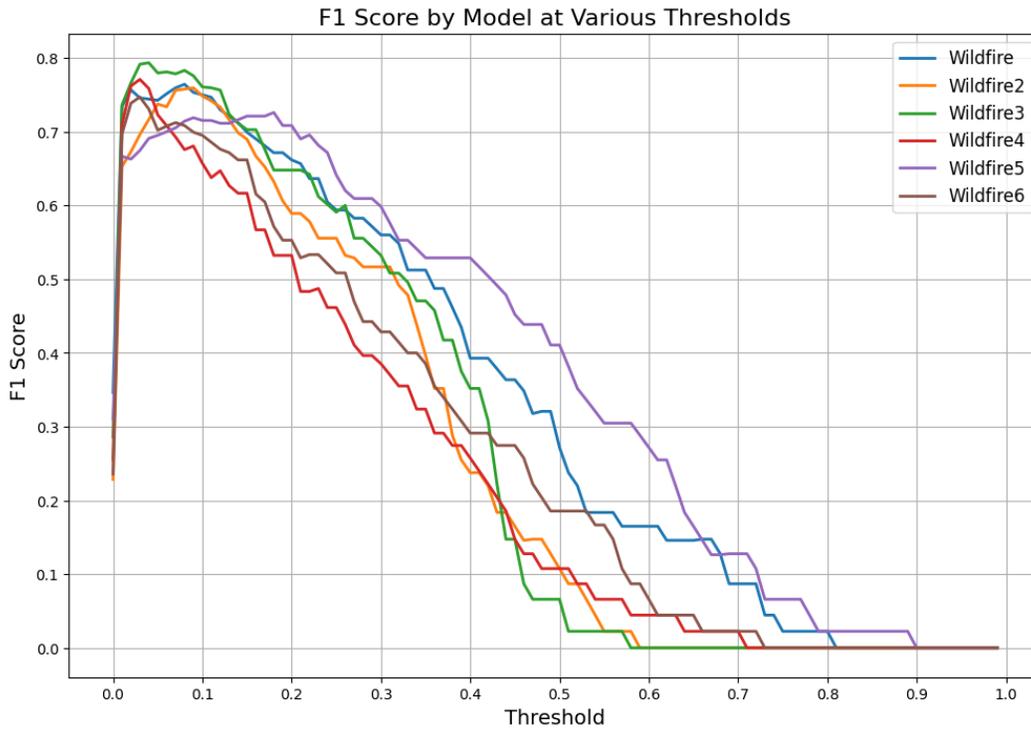


Figure 2: F1 Score by Model at Various Thresholds

Model	Threshold	F1 Score	Recall	Precision	Batch Size	Epochs
Nemo3	0.02	0.899	0.950	0.853	64	100
Nemo	0.03	0.893	0.929	0.860	32	100
Nemo4	0.05	0.886	0.899	0.873	64	50
Nemo6	0.06	0.880	0.882	0.878	32	50
Nemo2	0.17	0.883	0.873	0.892	16	100
Nemo5	0.03	0.877	0.912	0.845	64	50

Table 6: Optimal Thresholds and Corresponding F1 Scores, Recall, and Precision for Nemo Models, Sorted by F1 Score

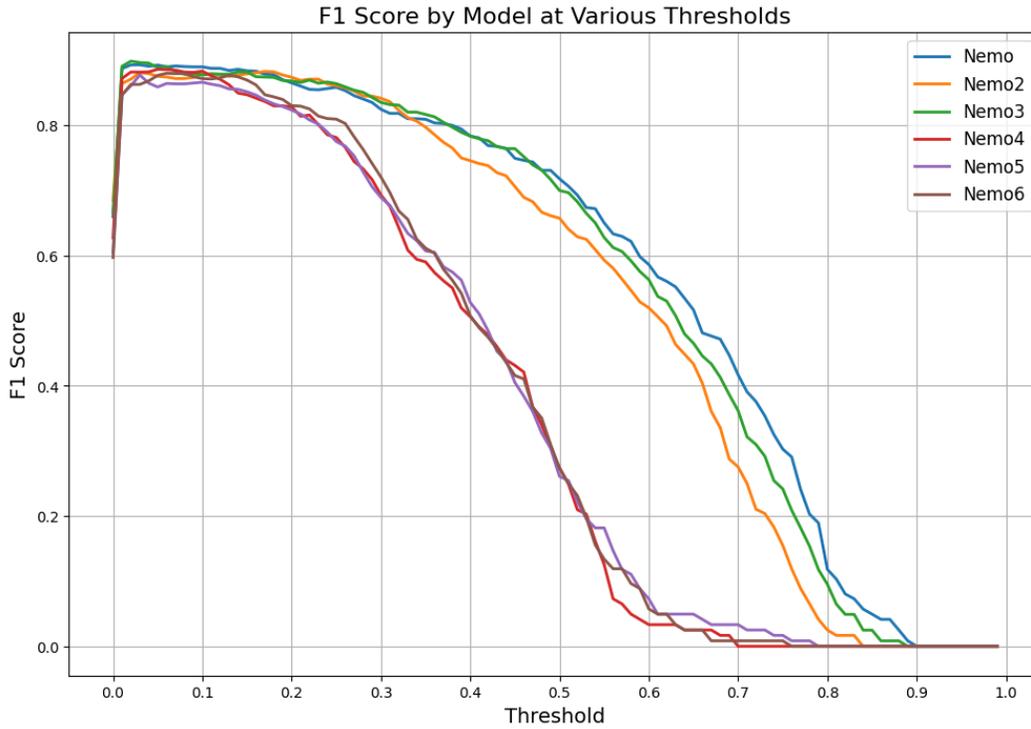


Figure 3: F1 Score by Model at Various Thresholds

Model	Threshold	F1 Score	Recall	Precision	Batch Size	Epochs
Fuego	0.02	0.623	0.497	0.835	32	100
Fuego4	0.01	0.502	0.856	0.355	64	50
Fuego5	0.01	0.458	0.574	0.380	16	50
Fuego3	0.02	0.459	0.331	0.746	64	100
Fuego2	0.01	0.476	0.743	0.350	32	50
Fuego6	0.04	0.337	0.270	0.451	16	100

Table 7: Optimal Thresholds and Corresponding F1 Scores, Recall, and Precision for Fuego Models, Sorted by F1 Score

Model	Threshold	F1 Score	Recall	Precision	Batch Size	Epochs
Aiformankind2	0.03	0.883	0.849	0.919	32	50
Aiformankind3	0.03	0.878	0.854	0.902	16	50
Aiformankind5	0.05	0.868	0.810	0.934	32	100
Aiformankind	0.06	0.827	0.753	0.917	64	50
Aiformankind6	0.01	0.835	0.864	0.809	64	100
Aiformankind4	0.03	0.843	0.875	0.813	16	100

Table 8: Optimal Thresholds and Corresponding F1 Scores, Recall, and Precision for Aiformankind Models, Sorted by F1 Score

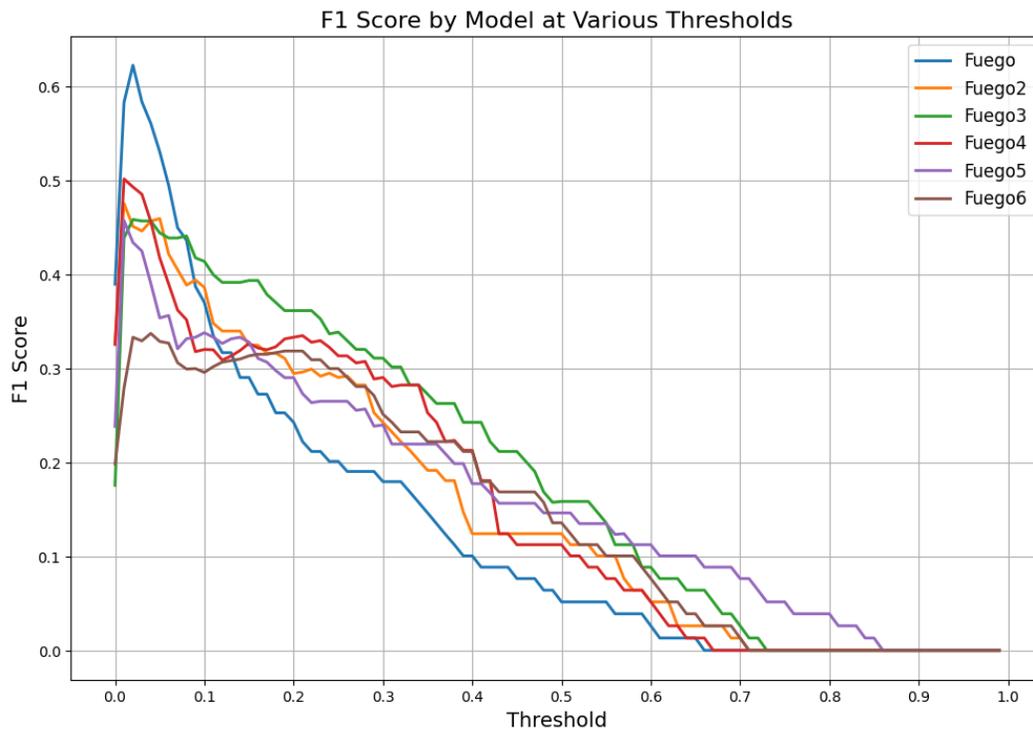


Figure 4: F1 Score by Model at Various Thresholds

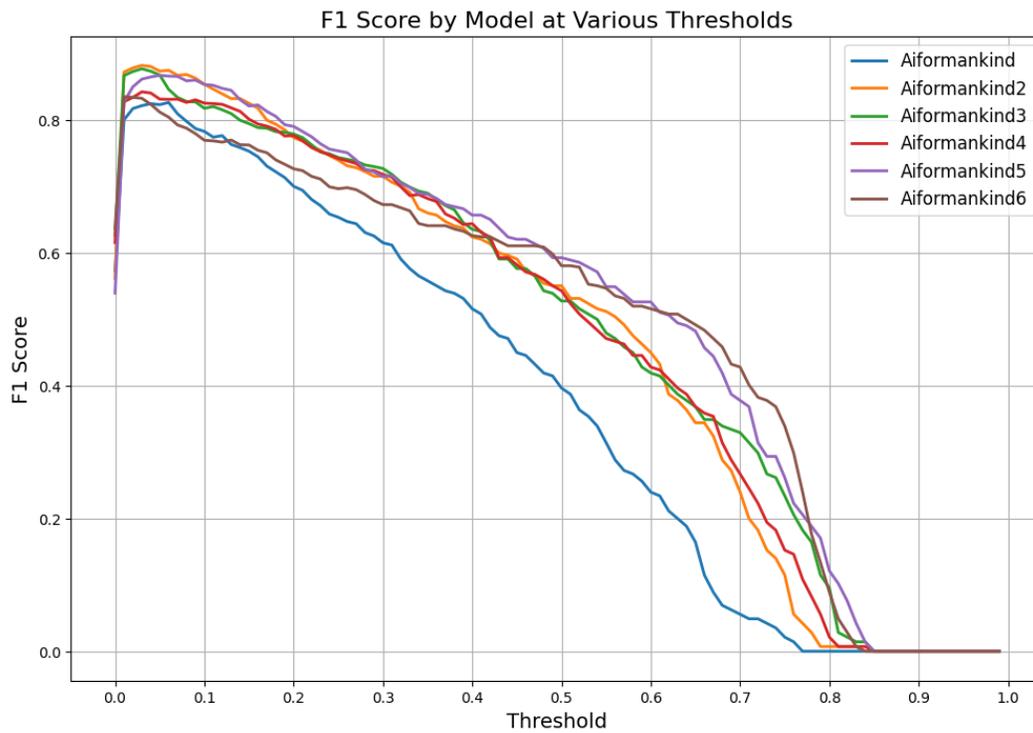


Figure 5: F1 Score by Model at Various Thresholds

Model	Threshold	F1 Score	Recall	Precision	Batch Size	Epochs
SmokeFrames3	0.15	0.920	0.887	0.955	32	50
SmokeFrames	0.1	0.901	0.901	0.901	16	50
SmokeFrames6	0.15	0.892	0.873	0.912	64	100
SmokeFrames5	0.13	0.887	0.887	0.887	32	100
SmokeFrames4	0.07	0.878	0.915	0.844	64	50
SmokeFrames2	0.19	0.870	0.845	0.896	16	100

Table 9: Optimal Thresholds and Corresponding F1 Scores, Recall, and Precision for SmokeFrames Models, Sorted by F1 Score

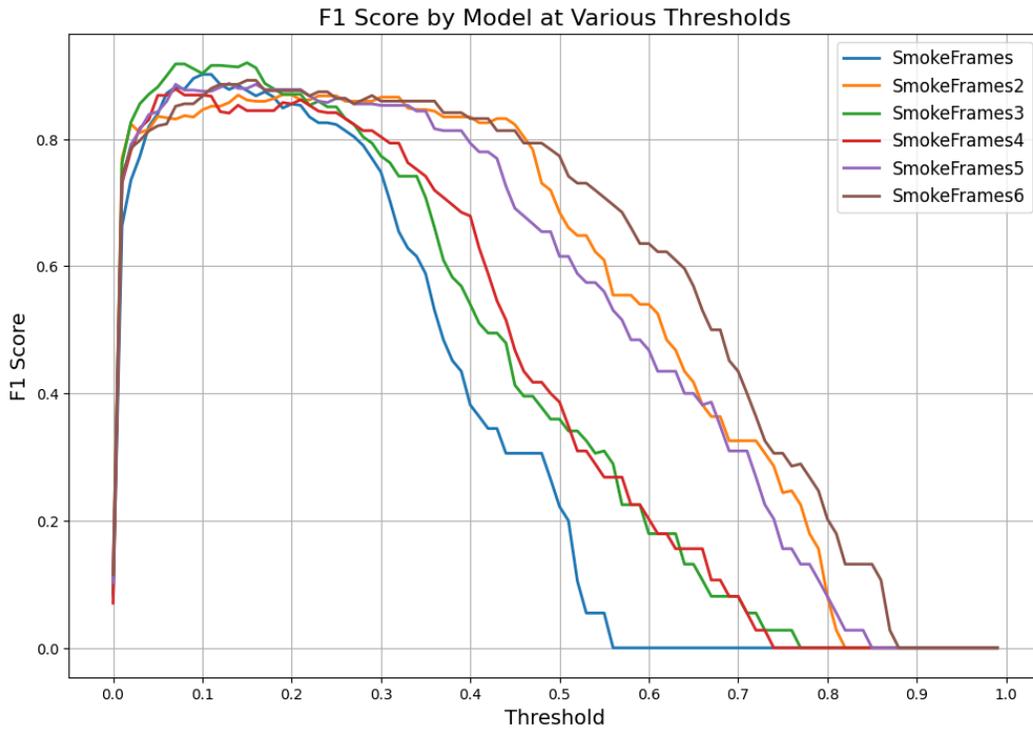


Figure 6: F1 Score by Model at Various Thresholds

Model	Best Threshold	F1 Score	Recall	Precision	Batch Size	Epochs
Combine3	0.05	0.871	0.884	0.859	32	100
Combine	0.05	0.867	0.877	0.857	64	100
Combine2	0.05	0.867	0.877	0.857	16	100
Combine4	0.04	0.861	0.865	0.856	16	50
Combine6	0.04	0.855	0.835	0.876	64	50
Combine5	0.11	0.851	0.807	0.901	32	50

Table 10: Performance Metrics of Combine Models Sorted by F1 Score with Corresponding Batch Size and Epochs