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Fire detection using few shot learning algorithms.

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A B S T R A C T :

Fire detection is a major application in the field of computer vision, requiring accurate and reliable algorithms for effective fire prevention and mitigation. This study deals with the use of few-shot learning algorithms, including Siamese network, Matching network and Prototypical network, for fire detection. A comparative analysis is conducted to evaluate the performance of algorithms on a fire detection dataset. The dataset is collected from different data sources and the dataset is divided into fire and non-fire category. The Siamese network achieved an accuracy of 82.50%, with a precision of 0.88, recall of 0.75, and F1 score of 0.81, demonstrating its robustness and effectiveness. Matching network and Prototypical network showed perfect scores across performance evaluation matrices (accuracy, precision, recall, and F1 score of 1.00), attributed to overfitting on the dataset. These shows the robustness of the Siamese network in fire detection and highlight the importance of addressing overfitting when using other algorithms.

Keywords: Fire Detection, Siamese Network, Matching Network, Prototypical Network, Few-shot Learning, Episodic Training.

Introduction.

In recent years, the occurrence of fire incidents has led to significant losses in terms of life, property, and natural resources. Early detection of fire can significantly reduce these losses by enabling rapid response. To address this problem and to provide the solution, the Fire detection systems acts as the major applications in the domain of computer vision which ensure the safety and helps in preventing the property damages.

Early and accurate detection of fires is crucial for minimizing these risks and enabling timely intervention by emergency services. However, traditional fire detection methods also exist such as smoke detectors and manual surveillance but they also suffer from some limitations. These methods can be prone to delays in detection or false alarms, especially in complex environments and those traditional fire detection methods rely on various sensors and algorithms, which, while effective, can sometimes be limited in their ability to generalize across different scenarios. With increasing the frequency of fire incidents due to climate changes or disasters, there is a growing demand for innovative solutions that can detect fires with speed, precision and accuracy.

Despite advancements in fire detection technology, there remains a challenge in accurately detecting fires in diverse environments using limited data. Existing methods often require large datasets for training, which may not always be available and challenging task to collect or gather those data. This is where advanced technologies, such as few-shot learning algorithms like Siamese network, Matching network and Prototypical network come into play. Few-shot learning offers a promising approach to developing intelligent fire detection systems, even in scenarios where labelled data is scarce. By developing and implementing these methods, we can improve fire detection capabilities in terms of speed, precession and accuracy, which can help enhance public safety, and reduce the harmful impact of fires on society and saves the property from being damaged.

This study aims to develop an advanced early fire detection system utilizing few-shot learning algorithms like Siamese Network, Prototypical Network, and Matching Network. These Few-shot learning algorithms offer a promising solution for this challenge by leveraging their ability to learn from a minimal amount of labelled data, these algorithms can rapidly adapt to new and unseen fire scenarios, providing more effective early detection capabilities.

The few-shot learning algorithms enable the fire detection models to learn patterns and make predictions from just a small number of labelled examples. There are also the various potential benefits to adapt this algorithms and those are :

1. Efficient Learning allow the model to generalize effectively with minimal data, making them ideal for rare or specialized tasks like fire detection.

2. Cost Reduction: Reduce the need for extensive data collection and annotation, saving time and resources.

3. Adaptability: Quickly adapt to new fire scenarios or environments without retraining on large datasets.

4. Robust Performance: They utilize advanced architectures, such as Siamese Networks and Prototypical Networks, to capture meaningful patterns even with limited samples.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature on fire detection and few-shot learning algorithms. Section 3 describes the methodology, including the data collection process and the implementation of the algorithms. Section 4 presents the results and analysis, followed by a discussion in Section 5. Finally, Section 6 concludes the paper with a summary of findings and future research directions.

Methodology.

2.1 The Dataset

Since the research deals with few-shot learning the dataset created for it also small but versatile in nature. It has been taken from various sources to including examples of raging fires, wild-fires , urban fires and small fires. The dataset consists of 314 images. For training the 294 images i.e., 152 images of fire and 142 images of No-fire and for testing 10 images of fire and 10 images of No-fire. The training data is normalized during training for more versatility and variability.

Fig(a). Example from the dataset of big fire, small fire and no-fire

2.2 Methods

The research methodology consists of three different algorithms: Siamese network, Matching Network and Prototypical Network. These methods are the main algorithms used for few-shot learning.

2.2(a) Siamese Network.

Siamese Network is a type of convolutional neural network (CNN) architecture which two or more identical networks for comparing similarity between the inputs, in this case images. EfficientnetB0 is used as the base architecture. EfficientnetB0 ensures better performance and efficiency for the model. The base architecture is primarily used for object classification and hence was an identical candidate for the research.

The creation and training of Siamese model consists of the following steps:

(i).Pre-processing: The images are loaded and normalized to get its pixels values between 0 and1 for applying machine learning algorithm. Further their sizes were changed for uniformity among them.

(ii). Creating image-pairs: Three types of image pairs i.e., fire-fire, fire-no_fire and no_fire-no_fire is created for training the Siamese network. The pairs created helped the model distinguish between fire and no-fire images.
(iii). Creating Siamese network: It consisted of using EfficientnetB0 as base architecture, as well as creating distance layer and freezing the last layer, putting custom last layer instead.
(iv).Creating support set and query set for episodic training : Support set consists of actual training data and query set consists of additional data (in this case images) for evaluating performance of the model and generalize to new examples.
(v). Episodic training: The episodic training refers to the training method in which various support sets and query sets are used to train a model to generalize to new data with as low data as possible. The episodic training yielded an accuracy of about 64% in this case.
(vi). Dataset training: Dataset training basically refers to supervised learning using the whole dataset using the same Siamese network. It helped the model to understand the overall trend, which the precision of episodic training wasn't able to capture. Hence it resulted in better performance.

2.2(b) Matching Network.

Matching network is also a type of model architecture based on Convolutional Neural Network (CNN). It focuses on learning similarity metric between data of query set and support set.

In this research, matching network is built using ResNet50 as the base-architecture. Further, layers were added for completion of the matching network.

The creation and training of matching network consisted of following steps:

(i). Pre-processing: It consisted of normalization and reducing image dimension to uniform size, same as was done in Siamese model.
(ii). Creation of matching network: The creation of matching network involved use of ResNet50 for extraction of embeddings. The embeddings are normalized for optimizing the process of calculating cosine similarity between support set and query set. Finally, softmax function is used to generate attention weights. All these parts made up the matching model.
(iii). Creation of Support set and query set: As done during the Siamese training, the support set and query set were created using the data set provided.
(iv). Evaluation: The model was then evaluated and the findings were recorded. The evaluation was done in format of performance metrics.

2.2(c) Prototypical Network.

Prototypical network focus on learning the representation space of the clusters from a particular class is formed. It helps in differentiating between objects of different classes. In the research, the EfficientNetB0 is used again for embedding extraction for prototypical network. It is a good and efficient resource for object classification.
The creation and training of prototypical network consisted of the following steps:
(i). Pre-processing: The data is normalized and standard size is selected for the images again.
(ii). Creation of the Prototypical Network: The EfficientNetB0 is used for feature extraction and Adam optimizer is also used for prototypical network.
(iii). Training the model using support set and query sets: In prototypical network, the creation of support sets and query sets was done simultaneously, while training the model.
(iv). Evaluation: The model is evaluated and the performance of the model is documented through performance matrix.

Results.

In our research, we evaluated the performance of three few-shot learning algorithms—Siamese Network, Prototypical Network, and Matching Network—on a dataset comprising fire and non-fire images. The Siamese Network presented a balanced performance with an accuracy of 82.50%, a precision of 0.88, a recall of 0.75, and an F1 score of 0.81. These metrics indicate that the Siamese Network was effective in detecting a proper fire instances while maintaining a good balance between precision and recall. On the other hand, both the Prototypical Network and Matching Network achieved perfect scores of 1.00 across all evaluation metrics, highlighting a significant overfitting issue. These models memorized the training data but failed to generalize to new, unseen examples. This underscores the need for further optimization of the Prototypical and Matching Networks to address overfitting and improve their real-world applicability. In contrast, the Siamese Network's more realistic and generalizable performance metrics suggest it is a more robust model for fire detection in practical scenarios.

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Accuracy: 82.50%
Precision: 0.88
Recall: 0.75
F1 Score: 0.81
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Fig(b)- Performance metrices for Siamese network.

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Accuracy: 100.00%
Precision: 1.00
Recall: 1.00
F1 Score: 1.00
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Fig(c) – Performance metrices for Matching network.

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Accuracy: 100.00%
Precision: 1.0000
Recall: 1.0000
F1-score: 1.0000
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Fig(d) – Performance matrices for Prototypical network.

Conclusion.

In this study, we chosen the domain of computer vision and we evaluated the performance of three few-shot learning algorithms—Siamese Network, Prototypical Network, and Matching Network—in the context of fire detection. The results revealed that while the Siamese Network demonstrated a balanced and generalizable performance with an accuracy of 82.50%, precision of 0.88, recall of 0.75, and an F1 score of 0.81, both the Prototypical and Matching Networks exhibited perfect scores across all evaluation metrics. However, these perfect scores indicate the issue of overfitting, where the models memorized the training data but failed to generalize to new, unseen examples. This study highlights the importance of addressing overfitting in few-shot learning algorithms to ensure their robustness and applicability in real-world scenarios. Future research should focus on refining the Prototypical and Matching Networks to improve their generalization capabilities and reduce overfitting, thereby enhancing their effectiveness in practical fire detection applications.

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