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Efficient Net: A Deep Learning Framework for Active Fire and Smoke Detection

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Abstract: In this paper, we propose a video-based model for fire detection using a model designed to detect fire and smoke after video processing. Then, the model was developed by increasing the rate of fire detection in a single image and using a pre-trained model. The real-time detection procedure is verified in 0.1 second. Also, an AI technique has been created to detect smoke and fire using deep learning (Effective Network). This is a more stable and faster technology than the current technologies in use. Like VGG16, VGG19, ResNet and the comparison was made with ResNet because it is better than other techniques. The results indicated that the proposed technique was better than ResNet.

Keywords: Fire Detection, Smoke Detection, Deep Learning, Efficient Net.

1. INTRODUCTION

Fires affect the environment in many ways. It is the main source of gas emissions that cause global warming and environmental changes. As well as the change in the size of the biomass in addition to the change in the hydrological cycle with secondary environmental effects. The smoke affects human and animal health and plants. For example, forest fires in the Amazon rainforest, which is the best biodiversity reserve on Earth, lead to a loss of biodiversity as well as biodiversity. The frequent fires are considered one of the great dangers that require an international effort to avoid material and human losses.

Early warning of the occurrence of fires in all places such as forests, factories, streets and tunnels is necessary and important to reduce the material and human losses caused by fires. The warning must be based on accurate and discreet detection of smoke. However, the classic techniques used in detecting fires such as smoke early warnings are considered bad in open spaces so it is difficult to warn of fires, and also from the negatives that result from the use of classic techniques are false alarms, delays in detection, and other negatives common. The

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effectiveness of any method must provide early warning of fires, as well as accuracy in warning. Therefore, researchers worked on many techniques for early detection of fires through methods of manipulating fixed cameras that detect fires in visible spaces as well as in the infrared field.
The detection of smoke through image processing as well as video clips of the areas monitored by fixed cameras. This technology is characterized by many good qualities, such as early detection of smoke from fires with high accuracy, as well as its simple practical installation, as well as the ability to effectively detect fires in large monitored areas. As for the processing of images captured by moving cameras or on board surveillance aircraft that monitor areas or forests, as well as drones, the processing must be with accurate and highly effective algorithms to detect and locate fires or smoke detection. The detection process must be characterized by rapid decision-making, as well as when the data is few, and the system must be characterized by ease in the detection process and in real time.
Manual smoke detection cannot meet the requirements of accurate detection and also needs a longer time. In addition, one of the most important challenges is changes in the shape, texture and color of smoke that are too complex to be detected in a particular image [1]. Likewise, most of the research and proposed methods in the literature try to detect the areas of smoke and classify them in the pictures, as the process requires specific and complex calculations. In addition, control devices are expensive (such as thermal cameras). In addition, these methods of detection depend on manual extraction of features and the implementation of classifiers according to these extracted features often leads to false alarm. Even if deep learning is used in image processing, these methods used in image processing require a lot of resources and a great deal of time to perform the calculations. Here, there was a need to suggest a method that combines feature extraction method (flicker analysis, energy, color, turbulence analysis, moving object analysis, etc.) and deep learning method. This proposed process leads to accurate and effective smoke detection at the lowest cost and time.

Literature Review

Smoke is the main clue to the existence of fire. Therefore, the researchers focused on the field of fire detection in general, which includes their work on the detection of smoke. At first, the various features of smoke were identified that were later relied upon. These properties and attributes are static or dynamic (color, movement, energy, texture, volume.) [2]. Many researchers have developed methods to ensure the necessary detection of smoke in the video. The first method is based on detecting smoke in the visible field [3]. In this area, the distance is less than 100 meters between the camera and the source. On the other hand, the second method [4] uses infrared images and deals with them. The third method is a combination of the two previous methods [5] for smoke detection.
Because of the high cost of infrared cameras, our research has focused on detecting smoke from fires in the visible field. We will review the methods of detecting smoke in the visible spaces. We will rely on the detection rate criterion and other criteria that we apply to research methods, which the higher the rate, the more successful, effective and reliable the method will be in detection. In the following diagram in Figure 1 shows the method of detecting smoke by extracting the feature that is the categorized vector that represents the features as a different set. Subsequently, smoke discrimination will adopt the necessary techniques for classification and the necessary segmentation algorithms.

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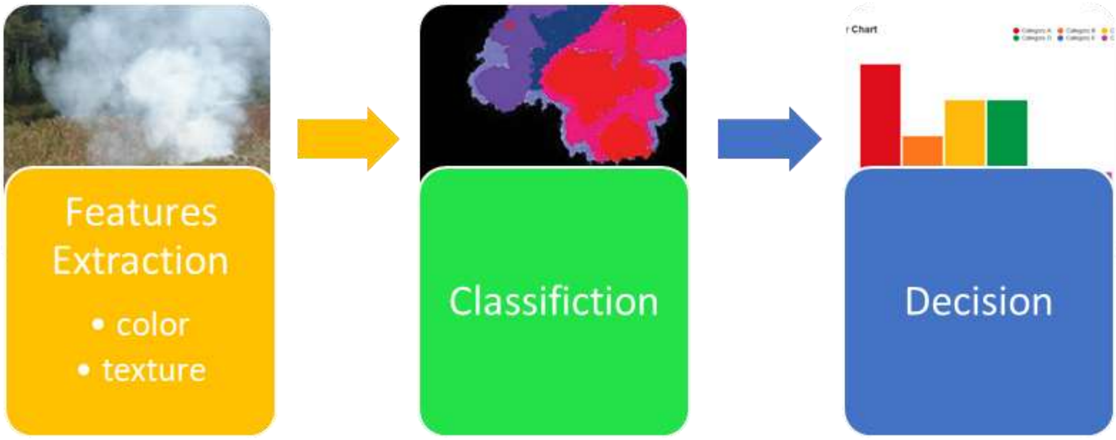

Figure 1: Process of smoke detection in classical methods.

While Borges et al [6] used a multidimensional vector as an important factor for the Bayes classifier. The attributes used are: Boundaries of Fire Zones, Roughness, and Moment Statistic which defines asymmetry, contrast, and amount of fire in images. An update of these ideas [7]. As noted earlier, all of these methods are rule-based and require feature extraction to detect fires and smoke. An important effective alternative is the use of deep learning techniques [6].
Celik et al [8] used two models: one for smoke detection and the other for fire detection. This model is based on the rules of fuzzy logic rather than the current disclosure rules. This method adopted for classification made it more effective by distinguishing between smoke and fire through colours [9]. As for smoke detection, a statistical analysis of smoke was used due to the appearance of a gray color with different backlighting [10].
Zhao et al [11] presented a new method for detecting smoke in photos and videos using CS Adaboost technology. First, the animation variables were extracted from two adjacent frames by a suitable background frame to avoid distractions, such as blue objects and gray objects.

The Deep Learning
There is no specific algorithm that is considered one of the best machine learning algorithms and it is effective for all applications that use image classifications. Which deals with huge data and many images, such as videos containing wildfires.

ResNet
ResNet is one of the deep learning algorithms, this algorithm solves a problem that occurs in training, when the network is saturated in terms of accuracy and then the accuracy declines rapidly (the disappearance of gradients) and also that adding in layers results in higher training error. Normalization is a solution to the problem of (the disappearance of gradients), the solution to this problem is in networks with few layers, and as for networks with very many layers [9], it reappears again.
The idea of the remaining connections (Fig. 1) is adopted in the neural network that is able to approximate complex functions. Therefore, we find that the approximation of the function H

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(x), which is the function formed from the previous layers, approximates the function $F\ (x)$. So the function $F\ (x)$ is $H\ (x)$ - x, given that the original function is $F\ (x)\ x$. Through job configuration and multi-communication through layers, the accuracy increases with the increase in the number of layers (network depth) and these networks are considered to have susceptibility to improvement [9].

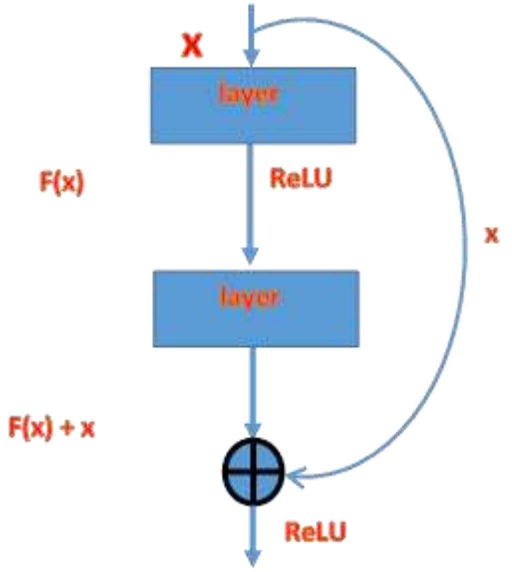

Figure 2: Remaining connections in the network.

EfficientNet

It is a group of models starting from B0 (main model) to B7 (larger model and high precision). An automated neural architecture method was used to construct the new convolutional neural network architecture. They called this structure EfficientNet. Today, EfficientNet is the most widely used and most accurate architecture of ImageNet [12].

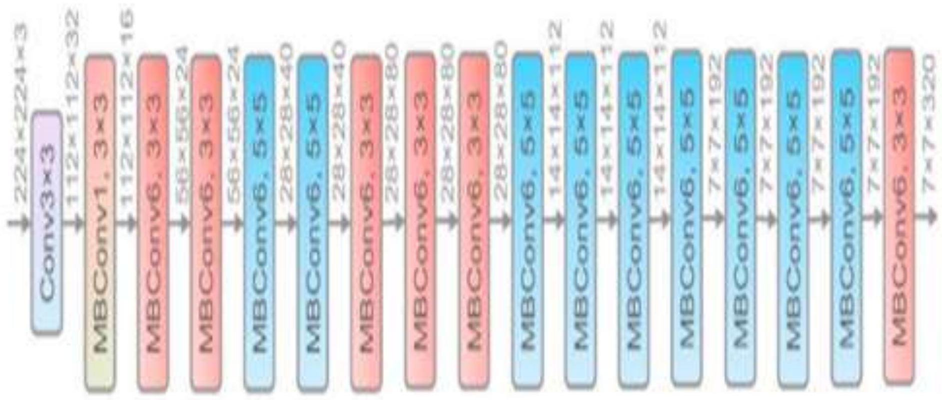

Figure 3: The network architecture of EfficientNet.

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EfficientNet architecture

The main architecture of the EfficientNet is EfficientNet-B0 (Table 1) where the first block is MBConv, followed by the "compression block". The EfficientNet-B7 model is architecturally the largest, hence the complex scaling is used [12], the complex scaling coefficients of the EfficientNet-B0 model are 1.2 = 1.2, β = 1.1, γ = 1.15.

Table 1: EfficientNet-B0 Architecture.

Stage	Operator	Resolution	Channels	layers
1	Conv 3x3	224x224	3	1
2	MBConv1 k3x3	112x112	16	1
3	MBConv6 k3x3	112x112	24	2
4	MBConv6 k5x5	56x56	4	2
5	MBConv6 k3x3	28x28	8	3
6	MBConv6 k5x5	14x14	112	3
7	MBConv6 k5x5	14x14	192	4
8	MBConv6 k3x3	7x7	320	1
9	Conv 1x1 & Pooling & FC	7x7	1280	1

Proposed Model

Many different data sets were analyzed using the proposed EfficientNet7 model, the first modular lightweight approach to fire determination. Quantitative and qualitative analysis was performed in four previously used data sets, using validation accuracy obtained during training of EfficientNet with all its subtypes starting from EfficientNet0 to EfficientNet5. ForestFire was an impressive and challenging dataset due to the large number of instances, embedded subsets, and smoke-tagged images. In the second place, the deep learning model aims to reduce the size and effectively recognize the fire in still images.

The architecture of EfficientNet7 is illustrated in Figure 3. The reason we chose EfficientNet7 as our critical learner is that it achieves a superior trade-off between efficiency and accuracy. In our model, the primary learner plays the most important role. This is because it is responsible for learning the image as well as for determining the detection process, meaning that its decisions are important in determining the final results directly. And also it is important that it be high efficiency, otherwise it will slow down the speed of the whole model.

The feature map can be output with deep semantic information because the input data flows through the multi-layer network. Our model in the real-world fire detection process, we need to deal with different datasets of fire and smoke, which are affected by the environment, in shape, texture or even color, which make up great difficulty for our learned model to extract effective features.

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Table 2: The computational cost of each model.

No.	Model Input Size	Flops	Parameters
1	ResNet	78.85M	148.91K
2	EfficientNet0	22.59M	186.25K
3	EfficientNet3	753.50M	345.53K
4	EfficientNet5	8.98M	676.82K
5	EfficientNet7	948.95M	986.23K

In table 2: The results were averaged from 20 times of training implementation after cross-data set validation. As for the results gained from FireSense and ForestFire with themselves, the dataset was split at 80%/20% for training and validation, respectively. For FireSmokeDataset, 620 images were used for training and 210 images for validation. For FireDataset, it was split at 70%/30%. The data sets used in training are in the rows, and in the columns are the data sets used for validation.

Figure (4) shows the accuracy of the results obtained after applying the model (EfficientNet7) to the data set (FireDataset) and it shows through the graph that the model (EfficientNet7) outperforms all other models and this indicates the success of the proposed model on this data set. As well as the rest of the figures (5, 6, 7), the results of other tests appear on other data sets, which we obtained by testing the models on different data.

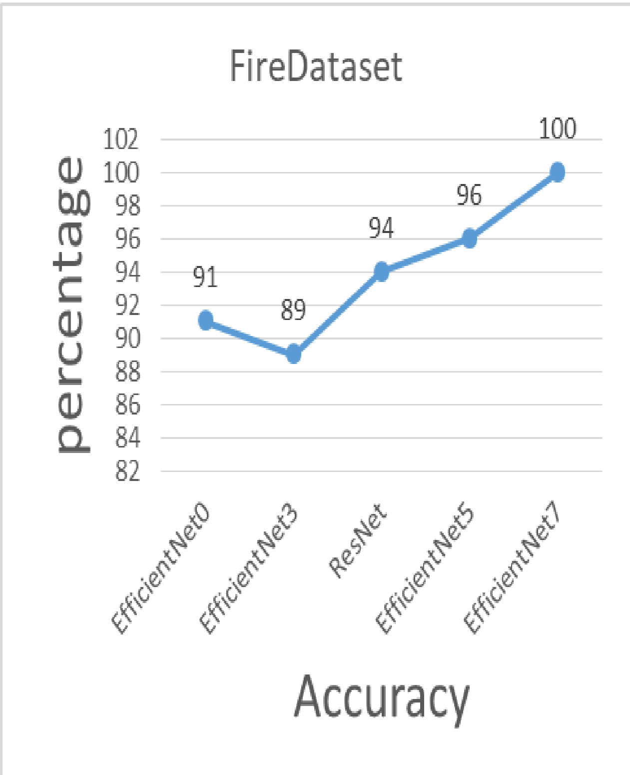

Figure 4: Accuracy of Models for FireDataset.

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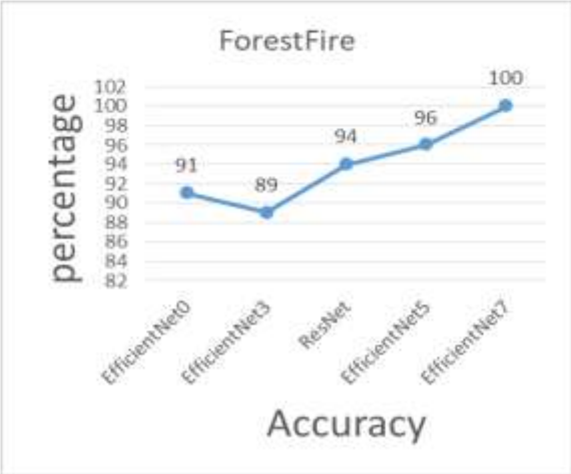

Figure 5: Accuracy of Models for ForestFire.

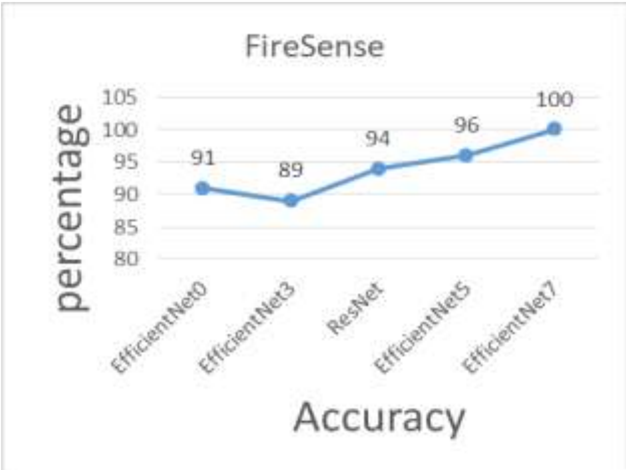

Figure 6: Accuracy of Models for Fire Sense.

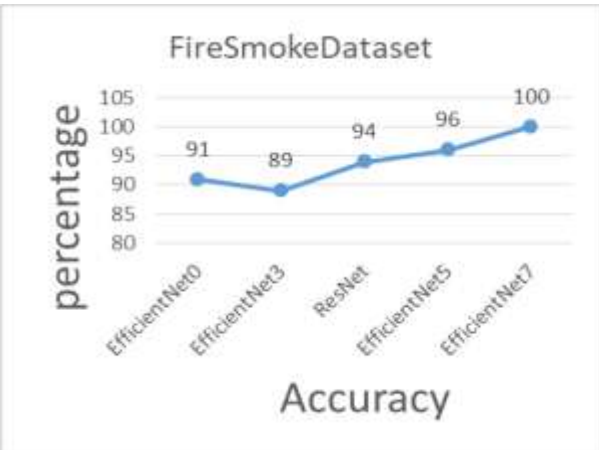

Figure 7: Accuracy of Models for FireSmokeDataset.

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EfficientNet7: Afirst lightweight approach

A novel family of object detectors called EfficientDet was created by Google, and it routinely outperforms prior art efficiency under a variety of resource limitations. In real-world applications, EfficientDet is frequently utilized and, like Yolov5, excels on tasks requiring Microsoft COCO and Pascal VOC. Its construction was altered to make it speedier and lighter than before.

The first results obtained from the EfficientNet7 model are relevant to the FireDataset, ForestFire, FireSense and FireSmokeDataset datasets. The goal of the methodology used to validate the data set is to select the best set of data to use in determining the fire. Use a complete data set for training and a second set for validation to measure generalizability while optimizing the model. Then, the training and validation phases are carried out by splitting one data set into two validation phases. The average results obtained by EfficientNet7 in each data set are shown in Table 3. In Table 3, the columns and rows show the application of the proposed algorithm after training it on a data set and applying it to the same group and to other data sets.

Table 3: Averaged EfficientNet7 Results with Cross-Dataset Validation.

Dataset	FireDataset	ForestFire	FireSense	FireSmokeDataset
FireDataset	100% ± 0.0%	83.87%± 0.89%	69.84%± 2.87%	70.71% ± 3.21%
ForestFire	84.43%± 1.08%	98.78%± 1.21%	91.65%± 2.08%	82.59% ± 1.21%
FireSense	86.43%± 1.29%	100%± 0.0%	99.47%± 0.12%	89.90% ± 0.69%
FireSmokeDataset	89.29%± 1.58%	95.09%± 0.50%	86.94%± 0.81%	99.44% ± 0.42%

In the table above, the model (EfficientNet7) was applied more than 10 times on different data sets, and then the average of the different results was taken, and the accuracy of the results was proven on the stability of the level of model implementation, which leads to positive and reliable results when applied to another data set, so there is a possibility for this model To become an important alarm on the presence of fires. The approved structure is light in implementation and predicts the presence of fires and smoke.

Evaluation

In order to statistically compare various architectures, we take into account the true positive rate (TPR), false positive rate (FPR), F-score (F), Precision (P), Accuracy (A), Complexity (number of parameters in millions, C), the accuracy to parameter ratio (A:C), and the throughput in frames per second (fps) that can be achieved Full-frame binary fire detection results are presented in Table 4. With the results in Table 4, we present only the best-performing variations of the reference structures (middle). The results show that when compared to other constructs, the variant proposed for datasets 1, 2 and 3 performs better in

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terms of accuracy and TPR (A: 0.96, TPR: 0.95) (Table 4, bottom). Dataset 3 and Dataset 4 together with the proposed algorithm are the two proposed architectures that provide the fewest number of false positives (FPR: 0.07).

Table 4: The architecture of the classical and proposed group algorithms.

Architecture	TPR	FPR	F1	P	A
VGG16	0.92	0.09	0.93	0.93	0.92
VGG19	0.84	0.03	0.90	0.97	0.89
EfficientNet7	0.95	0.04	0.96	0.97	0.96

4. CONCLUSION

The detection of fire and smoke is an important and necessary process and the results must be honest and real to prove the efficiency of the system, so the results obtained show the following, EfficientNet7 achieved high accuracy in small data sets. However, generalizing large data sets is very difficult because there are many similarities. The lack of parameters does not adversely affect the overall model. Among the datasets that were used, FireSense provides more images than the others, and is also suitable for use with the ForestFire dataset for the fire classification process due to its large data. The FireSmokeDataset is suitable for smoke detection operations, which can also be used to identify fires.

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