

ORIGINAL RESEARCH ARTICLE

DSRO based data annotation with improved EfficientNet for forest fire detection using image processing in IoT environment

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ABSTRACT

The increasing risk of forest fires demands sophisticated detection systems in order to mitigate the environment effectively. The technology under consideration enhances real-time monitoring and reaction by functioning inside an Internet of Things (IoT) architecture. Even though Artificial Intelligence (AI) algorithms have improved fire detection systems, they are quite expensive and energy-intensive due to their high computing needs. With the use of creative methods for data augmentation and optimization as well as a shared feature extraction module, this research study offers a thorough fire detection model using an improved EfficientNet that tackles these issues. Three technical components are creatively combined in the realm of forest fire detection by this study. The first stage is the use of diagonal swap of random (DSRO) data annotation, which makes use of spatial connections in the data to improve the model's understanding of complex aspects that are essential for precisely identifying possible fire breakouts. By adding a shared feature extraction module across three functions, the second stage solves difficulties in feature extraction and target identification. This greatly increases the model's performance in complicated forest scenes while reducing false positives and false negatives. The third and final stage focuses on improving the EfficientNet model's capacity for accurate forest fire categorization. When taken as a whole, these technical components upon creative combination improve the existing technology in forest fire detection and provide a thorough and practical strategy for reducing environmental hazards. For the purpose of hyperparameter tuning in the EfficientNet for the classification of forest fires, an improved Harris Hawks optimization (HHO) is used. By using the Cauchy mutation approach with adaptive weight, HHO expands the search space, boosts population diversity, and improves overall exploration. By including the sine-cosine algorithm (SCA) into the optimization process, the likelihood of local extremum occurrences is decreased. The proposed strategy is successful compared to other existing models, as shown by the experimental findings that show an improvement of 5% in accuracy compared to the standard existing model, and an improvement of 2% compared to EfficientNet model in detecting forest fire.

Keywords: forest fire detection; improved EfficientNet; Harris Hawks optimization; sine-cosine algorithm

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1. Introduction

One of the most crucial components of any early warning system is the ability to detect and report fires in the area under surveillance. Smoke and fire detectors are installed to alert people as quickly as possible in the event of a fire. Present-day smoke and temperature detectors are the norm^[1]. The sensor will be less effective and will incur high costs if it is installed in a forest, a highly populated community, or on a road. Additionally, delays and alarm sound faults are common issues with traditional fire detectors. To put it another way, communities are increasingly relying on video surveillance to keep their residents secure. Early fire discovery is a challenging but

vital topic because of its influence on public security and the environment. The early finding of fires is crucial in modern technology for the prevention of injuries and property loss^[2]. “Wildfires are becoming more intense and frequent, ravaging communities and ecosystems in their path,” says the United Nations Environment Programme. Without prompt intervention, wildfires can burn for days, causing a climatic disaster and human casualties^[3]. The climate problem has already begun to influence the stability of the world’s water supply, the average temperature, and the fate of certain endangered species^[4]. For this reason, we can’t afford to treat wildfire issues lightly lest they spiral out of control. Numerous issues can be mitigated by installing fire detection systems by forest department^[5]. Image-based fire detectors, unlike traditional smoke alarms, don’t need to be installed in tight spaces, reducing installation and maintenance expenses. The characteristics utilized to differentiate fire from other objects have a significant impact on image-based fire detection^[6]. There are two main classes of fire detection features: those that require human intervention and those that do not. Features that are handcrafted follow a set of guidelines. Things like movement, form, color, and texture are all examples of such characteristics. Meanwhile, the fire must be identified in the early stages itself^[7].

The economic and resource losses caused by forest fires are compounded by the risk they pose to human life and public infrastructure. Putting out forest fires is difficult and dangerous work at the moment^[8]. That’s why it’s so important to find fires promptly and put them out before they spread. Manual examination and regular sensor monitoring have been the mainstays of forest fire past^[9]. Manual examination, on the other hand, necessitates not just time and effort but also precise knowledge of where the fire is^[10]. Because of their low cost, wide coverage, and efficient identification^[11], sensors are increasingly being employed in forest fire detection because of recent advancements in computer technologies. Studies using visible, infrared, hyperspectral, multispectral, and 360-degree cameras, all types of optical sensors, have shown promising results in detecting forest fires^[12]. In addition, there is ongoing development in the hardware and software used to spot forest fires. Watchtower monitoring and satellite remote sensing were initially the foundations upon which forest fire detection systems were built. But watchtower surveillance is too rigid, and satellite photos are too big for early forest fire detection^[13].

These days, in several fields the technology has shifted towards the use of Internet of Things (IoT)^[14]. Micro-Electro-Mechanical systems (MEMS) technology allows miniaturized devices to be controlled over the internet^[15]. Messages regarding fire hazards can be sent using the IoT framework^[16]. Among the numerous applications where deep learning has proven superior to conventional approaches is the detection of forest fires^[17]. Non-manually constructed characteristics have been employed in several recent research for fire detection. The generative adversarial network (GAN), YOLO, SqueezeNet, etc.^[18] are all examples of deep learning architectures designed to address the issue of sparse data. Non-handmade feature resulted in improved fire detection accuracy compared to handcrafted feature results. However, the computing time required by non-handmade features is typically higher than that required by handcrafted features. In order to identify fires, some researchers sought to blend manually generated and automated characteristics^[19]. Many image classification techniques, object identification models, and semantic replicas have been implemented in prior research on forest fire detection^[20]. Only a small number of research have looked at the synergistic benefits of combining various approaches. Our study creatively combines three technical components as follows:

- This paper presents an enhanced EfficientNet model for forest fire detection, which improves the model’s feature extraction and learning skills from small data.
- The SCHHO model, which combines sine-cosine with the Cauchy mutation approach, is used to choose hyper-parameters optimally. The model is employed to enhance the suggested algorithm’s capacity for exploration, and an adaptive weight is provided to enhance the procedure’s ability for exploitation.
- The detection of tiny flame targets, especially the viewpoint’s edge, can be made better by the use of a data augmentation policy that involves a diagonal swap of chance origin.

The various sections of the paper are laid out as follows: The literature review and associated problem statement are presented in section 2, and the suggested model is described in section 3. In section 4, we examine the results of the experimental investigation. The study's findings and recommendations for the future are summarized in section 5.

2. Related works

Using deep learning approaches, Abdusalomov et al.^[21] introduced a unique approach to categorize forest fires based on the Detectron2 platform. For the training phase, a custom dataset was created and labelled, which resulted in higher accuracy than rivals. With a unique dataset of 5200 photographs, the Detectron2 model was refined via many testing situations, yielding a strong performance. The recommended approach proved to be able to identify even the tiniest flames at a great distance, especially at night. The benefit of the Detectron2 algorithm is its long-range target detection capability.

Building on the work of YOLOv5, Lin et al.^[22] developed the TCA-YOLO forest fire detection model. This model combined a transformer encoder with a CNN network, using the coordinated attention (CA) method to target certain objects. By reducing the amount of human labelling required, semi-supervised learning was used, leading to better global information extraction. The model demonstrated improved targeting precision, improved extraction of global data, and decreased susceptibility to perturbations from targets that resembled wildfires. Its effectiveness was shown by the fact that, at a fast frame rate of 53.7, it was especially successful in identifying tiny forest fires.

Using IoT devices, Avazov et al.^[23] showed how cooperative efforts may be made online to remedy missing or erroneous alerts provided by YOLOv5. After receiving these reports, the fire department looked into the matter further. Using widely used performance criteria, the method's fire classification test results were compared with those of other previously published systems.

The GXLD defogging technique was suggested by Huang et al.^[24] and uses the dark channel to produce sharp pictures. Using GhostNet, depth, and SENet-modified YOLOX-L-Light, fires were detected in images of clear forests without fog. Mean average precision (mAP) was used to test detection accuracy, while decreased network features were used to evaluate its lightweight effect. In trials using simulated forest fires, GXLD showed a marked decrease in number of components, boosting mAP by 1.96% with an average fps of 26.33. GXLD demonstrated precise real-time forest fire detection even in severe fog, exhibiting an efficient lightweight fog-free system.

Using a multi-scale approach, Zhang et al.^[25] enhanced the faster RCNN target identification model for the detection of forest fires. In the MS-FRCNN model, ResNet50 took the role of VGG-16 as the backbone network. ResNet50 addressed issues with gradients and combined with FPN to provide better feature mapping. Background interference was decreased by FPN by improving the RPN and concentrating on semantic and target forest fires. By using a soft-NMS approach to reduce frame deletion errors, the MS-FRCNN model outperformed baseline models in small target forest fire detection.

Grid RCNN proposed by Lu et al.^[26] is a CNN-based method that used grid guided procedure for object identification. Compared to conventional methods Grid RCNN uses spatial information along with convolutional architecture. The model has been successfully used to identify forest fires, demonstrating its use as a timely reaction and preventative tool in real-world scenarios.

A technique for detecting shadows on the battlefield, spotting forest fires, and wirelessly sending data to a command centre was created by Kaur et al.^[27]. In order to guarantee sensor node (SN) availability and prolong the lifespan of wireless sensor networks (WSNs), the EEWBP approach was proposed. A composite weighted metric that took neighbor nodes, average flying speed, and trust value into account was used by EEWBP.

Simulation results indicated that EEWBP worked better than CH consistency, CUCA, CACP, CPCP, and DDOS, boosting packet delivery rate and postponing network node depletion.

The integrated sensor system (ISS), a group of sensors that provide essential information for fire forecasting, was suggested by Almasoud^[28]. An attention-based convolution neural network with memory, the ACNN-BLSTM model, examined and verified the possible damage. The ACNN-BLSTM model's detection performance was improved by hyperparameter tinkering using bacterial foraging optimization (BFO). The GSM modem alerted the authorities to the fire, and simulations showed that the IWFFDA-DL technique improved the situation in many ways.

A camera system installed atop towers was devised by Prasanna et al.^[29] in order to detect forest fires in their early stages. A long range network (LoRa) with a built-in fire-finding algorithm alerted the forest service by sending signals depending on the exact locations of nodes. At the furthest points of node networks, fire detection systems were connected to regional forest management centers via gateway connections and internal Internet access. LoRa's wide broadcasting range allowed the system, which was powered by distributed solar arrays and had a very small power footprint, to provide vast coverage.

A multimodal method was put up by Vikram and Sinha^[30] to locate flammable areas in woods. The approach divided the forest into sections, each of which included two kinds of sensors: a real-time video sensor and a sensor for temperature, humidity, and dryness. Every sensor data, including picture data, was sent to a single hub, from which the Multimodal station calculated the state of the forest zone. By integrating sensor perfect with a CNN model, the framework exhibited greater fire detection accuracy compared to individual Sensor and Image prototypes. This allowed the control center to minimize forest damage by acting quickly to avert fires.

YOLOv5s-CCAB, an improved fire identification model, was presented by Chen et al.^[31]. By adding coordinate attention (CA) to YOLOv5s, the network's attention was adjusted to concentrate more on the features of forest fires. In order to more accurately detect forest fires, the core network included contextual transformer (CoT) and the CoT3 module. For further improvement, the intersection-over-union (IoU) loss function was changed. Results from experiments proved that the suggested model works well.

Problem statement

Wildfires are damaging, destructive, more frequent and inflicting havoc on ecosystems & communities, as reported by the United Nations Environment Programme (UNEP). There are several causes of wildfires. It's either owing to naturally occurring bushfires or due to carelessness on the part of humans. Wildfires can be contained if bushfires are discovered in their early stages. In addition, we may avoid such incidents by stopping individuals as they kindle a fire. Some studies on forest fire alarms were discovered throughout the investigation. However, we did find several potential problems that they may encounter.

- One common method for detecting a fire is by the use of sensors. But relying just on a smoke detection sensor might result in false alerts, as several odors, not just smoke, can be present.
- Some alternative fire detection systems employ remote cameras to detect an actual fire. The cameras in this type of surveillance need to be constantly monitored by humans, who may or may not be able to resist drifting off to sleep.
- It is also possible to efficiently detect and prevent fire disasters using R-CNN-based methods. However, there is a chance that this technique will occasionally make mistakes and mistakenly label candidate fire zones as actual fires. As a result, they might cause unnecessary alerts.

Finding these issues in prior studies and the scope to improve, inspired us to develop the proposed system. In the next section we discuss about the proposed system in detail.

3. Proposed system

The described technique has two primary goals: (1) faster Forest Fire identification and (2) notification of the appropriate rescue authority. First, there is a camera hooked up to validate the real fire pictures seen by the flame, smoke, and heat detectors. The controller would then, depending on the severity of the blaze, immediately activate the sprinkler system, sound an alarm and contact the appropriate authorities.

3.1. Integrated sensor system

This strategy uses a combination of detectors rather than just one. This detector is a primary data contributor to the fire detection. The detector's output is combined with images from a digital camera. The full intelligent fire detection technique is decided for giving extremely exact detection by combining these two approaches.

3.2. Micro-controller

The GSM, ISS, and picture processing components are all combined into a single, streamlined device. Socket programming with a Wi-Fi shield aids wireless transmission in the proposed approach. For instance, a forest area may contain several ISSs. Each ISS has a unique identification number and associated geolocation information. It uses this information to pinpoint where the fire started. The microcontroller sets a threshold to activate the multi-data fusion procedure. It takes in data from several sources and determines the best approach for perceiving potential fires. The strategy sorts the processed findings by urgency and sends them on to the rescue authority.

3.3. Dataset description

In this research, the implementation of the method relies heavily on the excellence of the data set preparation. In order to compile the dataset, we used photos from a number of publicly available sources, such as VisiFire^[32], ForestryImages^[33], FiSmo^[34], BowFire^[35], Firesense^[36], and Dataset^[37]. There are photographs of natural forests that have been disturbed, as well as day and night fires, aerial fires, fixed shot fires, mountain fires, surface fires, trunk fires, canopy fires, etc., in this self-built data collection. There were 6500 photos in the dataset, 3900 of which showed forest fires and 2600 of which did not. To facilitate the training and testing procedures, we arbitrarily split the total dataset into two halves, an 8:2 training set and a 2:2 validation set. **Figure 1** displays a selection of typical images containing forest fire. **Figure 2** displays a selection of typical images not containing any forest fire.



Figure 1. Examples of the data set containing imagery of forest fire.



Figure 2. Examples of the data set containing imagery of no forest fire.

3.4. Pre-processing and annotation

This criterion seeks to train the model using a wide range of photos while minimizing the risk of it mixing together disparate but related situations like, say, a sunset in a mountainous or forested environment. The dataset should be fine-tuned for optimal mode training and enhanced results. Therefore, we investigated the dataset and carried out the required pre-processing, such as trimming just the photographs that were relevant to the intended problem, such as a picture portraying a fire on a mountain or in a forest. After that we cropped the photographs, resized them all to the same 224 by 224 pixel resolution. These initialization procedures simplified and expedited the model's training on forest fires.

There were three types of annotations applied to each image in the dataset. Annotation for the complicated and obligatory some cautions, whereas picture classification labelling was done during collection. Using the LabelImgtool^[38], we annotated a rectangular box around the flame area so that it could be used for object recognition; the four corners of this box were required to precisely match the flame target within a tolerance of two pixels. Using the polygon annotation feature of the pixel-level Labelme tool^[39], we were able to create a rough outline of the flame target for use in the segmentation process. **Figure 3** displays an illustration of data annotations.

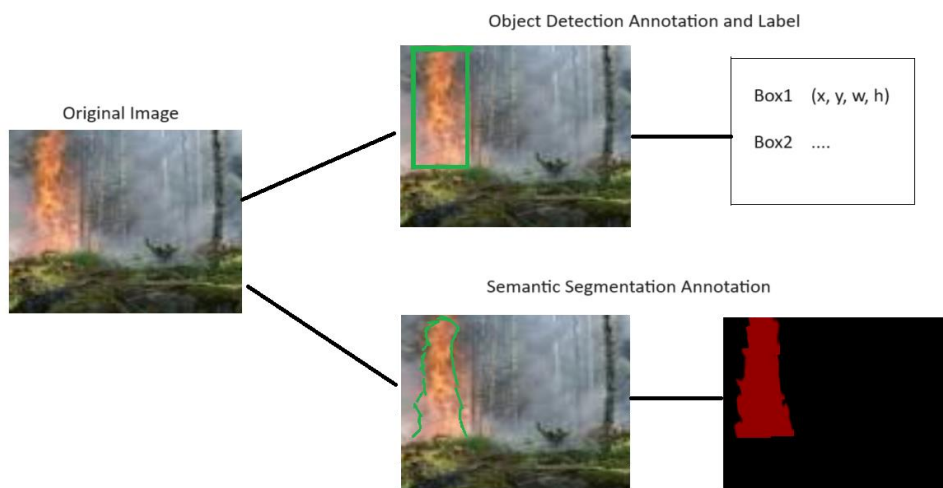


Figure 3. An illustration of data annotation.

Since the model is comprised of several distinct processes, it pooled their individual strengths to recover accuracy and efficiency. Despite the commonality of feature removal and feature fusion modules, feature

utilization and task specificity distinguish segmentation and detection tasks. While the object detection task employs regression boxes to differentiate across regions, the semantic segmentation job uses pixel points to focus on fine-grained category distinction.

3.5. Augmentation of data

The research shows that existing algorithms struggle to accurately identify tiny flame targets, such as those that are obscured or appear towards the image’s boundaries owing to camera or perspective constraints. The low sum of tiny targets in the forest fire data set and the limited amount of pixels capable of representing such objects’ attributes are to blame. Therefore, we used a data augmentation strategy, to improve the finding of tiny targets in forest fires.

The strategy is rather straightforward, yet it works. First, it checks to see whether there is a single label for a target in the graph, and second, it sees if that target is a medium-sized item. The picture is then quadratically split depending on the origin, which is generated randomly in the region label width and height height as depicted in **Figure 4**. Then, a new picture is formed by switching the positions of the two diagonal images. This method not only enhances the model’s generalizability by including more tiny targets but also of cases with inadequate models of flame targets due to perspective limits.



Figure 4. Diagram of data augmentation using slanting swap of chance origin.

The photographs collected from forest fires are rather varied. However, because only a subset of possible pictures is included in the dataset, the trained perfect may struggle to generalize to new, unseen data. To ensure that the dataset is representative of a wide range of pictures, it augmented the training dataset with image transformations such as scaling, rotation, translation, and magnification. **Table 1** details the enhancements made to the dataset.

Table 1. Data augmentation.

Value	Augmentation
1°~50°	Revolution
0.1~0.2	Scaling
0.1~0.2	Shear transformation
0.1~0.2	Translation

3.6. Classification using improved EfficientNet-B0 pre-trained model

The size and complexity of Efficient Net’s convolutional neural network are both scalable thanks to the usage of a compound coefficient. This combined coefficient scales the parameters of depth, breadth, and

resolution equally, guaranteeing that the network will always look the same. The Efficient Net scaling strategy uses a predetermined set of scaling coefficients to consistently modify the resolution, breadth, and network, as opposed to the conventional approach of uncontrolled scaling of these parameters. Compound scaling is based on the idea that a network needs more layers and channels to detect finer details in a larger input picture and more layers to widen its receptive area as the input image gets bigger. **Figure 5** depicts the EfficientNet-B0 model’s design.

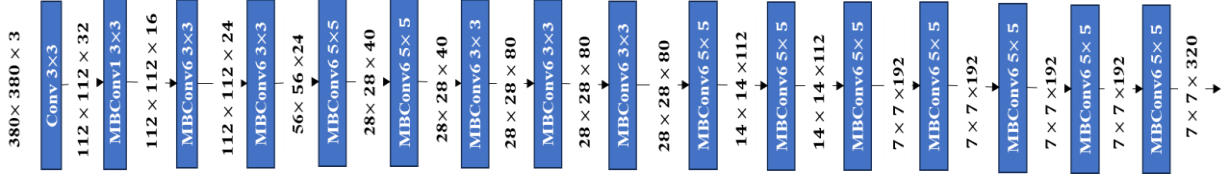


Figure 5. The architecture of EfficientNet-B0^[40].

Model tuning: The network was originally trained using over a million photos from the ImageNet dataset, which includes over a thousand distinct object classifications. For initial tuning, we left off the final three layers and substituted fully connected, softmax, and output layers. In this case, we employed the hybrid optimization technique described below to fine-tune the hyper-parameters. We set various hyperparameters, including the learning rate at 0.005, the momentum at 0.703, and the epochs at 100 before optimizing. Finally, we used deep transfer learning to train this optimized model.

The term “transfer learning” describes the process of acquiring expertise in a new area. Particularly in the field of medical imaging, deep learning’s need for massive amounts of training data makes it challenging to understand individual patterns. The “source,” represented above, is a labelled dataset.

$$F_f = (G_f, H_f) \quad (1)$$

where $H_f \in I^{r_1}$ is the label, and $G_f \in I^{\delta \times r_1}$ is a d-space. The r_1 is the total sum of source samples. The “target” dataset is recognized as $F_t = (G_t)$, where $G_t \in I^{\delta \times r_2}$ and r_2 are the total number of target tasters. There are two significant descriptions of shadows:

The two primary components of a “domain” $F = \{G, r(i)\}$ are the chin data G and the distribution $\rho(i)$, which has a variety of $[0, 1]$. One definition of a “task” is the set of labels H and the matching function $J(i)$ that predicts the labels H .

Deep features were recovered from the trained deep learning models utilizing deep transfer learning. **Figure 5** depicts the split-image training process used to create the refined model. The features were taken from the global average pool layers of the trained models. Following feature extraction, the improved forest fire photos had feature vectors with size N 1280.

3.6.1. Hyper-parameter tuning process of proposed model using HHO

Harris Hawk optimization (HHO) is utilized in this work to optimize hyper parameter tuning of EfficientNet-b0 classification. It uses a mathematical formula to model the tactics employed by Harris Hawks when hunting in a variety of environments and using a variety of capture techniques. Harris Hawk optimization (HHO) uses a candidate solution (Harris Hawk) to iteratively approach the optimal solution (HHO). The HHO algorithm consists of three processes such as exploration process, transition process and exploitation process. The transition of the Harris hawks from exploration process and exploitation process is based on the computation of prey energy.

A. Exploration process

During the Hawks randomly look for prey using one of two strategies: inspecting and monitoring the search space[LB,UB]. Based on probability p value, the location will be changed as follows:

$$P_{t+1} = \begin{cases} P_{rand} - k_1|P_{rand} - 2k_2P_t|, & p \geq 0.5 \\ (P_{prey}(t) - P_m(t)) - k_3(LB + k_4(UB - LB)), & p < 0.5 \end{cases} \quad (2)$$

where P_{t+1} and P_t are the positions of hawks. The constants k_1, k_2, k_3, k_4 and p are random statistics between 0 and 1; LB and UB are the bounds on search space. $P_m(t)$ signifies the average location of hawks.

B. Transition process

The transition of hawks from exploration process to exploitation process is dependent on the prey energy. Hawks switch from exploration process to exploitation process based on the energy of prey Ep_t as computed below:

$$Ep_t = 2Ep_0 \left(1 - \frac{t}{T}\right) \quad (3)$$

where Ep_0 is initial prey energy and a random number between -1 and 1.

When $Ep_t \geq 1$, the hawks will perform exploration, The transition process occurs when $Ep_t < 1$, the hawks will perform transition from the exploration process to the exploitation process.

C. Exploitation process

Exploitation process consists of 4 different stages as decided by energy parameter Ep_t and escape chance of prey denoted by parameter e .

Stage I:

When $Ep_t \geq 0.5$ and $e \geq 0.5$, the hawks prefer to drain their prey's energy slowly in gentle besiege. The method of positional updating is described by:

$$P_{t+1} = [P_{prey}(t) - P_t] - E|J \cdot P_{prey}(t) - P_t| \quad (4)$$

In the above equation prey's random escape jump is $J=2(1 - k_5)$ and the constant k_5 is a random statistic in $[0, 1]$.

Stage II:

When $Ep_t \geq 0.5$ and $e < 0.5$, hawks will set up a gentle besiege with a rapid dive. To mimic the predator's leaping activity and means of escape, HHO incorporates the Levy function (LF)^[41]. The position-updating approach is written as follows:

$$P_{t+1} = \begin{cases} A: P_{prey}(t) - E|J \cdot P_{prey}(t) - P_t|, & \text{if } F(A) < F(P_t) \\ B: A + R \times LF(N), & \text{if } F(B) < F(P_t) \end{cases} \quad (5)$$

$$\text{Where } LF(N) = \frac{0.01 \times \mu}{|\alpha|^{\frac{1}{\beta}}} \times \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{\frac{\beta-1}{2}}} \right)^{\frac{1}{\beta}} \quad (6)$$

In the above equations μ and α are random statistics in $[0, 1]$, $\beta=2$, N is dimensionality and R is a random vector.

Stage III:

When $Ep_t < 0.5$ and $e \geq 0.5$, the hawks will set up a harsh besiege to catch the low energy prey. The position-updating approach is written as follows:

$$P_{t+1} = P_{prey}(t) - E|P_{prey}(t) - P_t| \quad (7)$$

Stage IV:

When $Ep_t < 0.5$ and $e < 0.5$, the hawks will set up a harsh besiege with rapid dives. The method of positional updating is described by:

$$P_{t+1} = \begin{cases} A: P_{prey}(t) - E|J \cdot P_{prey}(t) - P_m(t)|, & \text{if } F(A) < F(P_t) \\ B: A + R \times LF(N), & \text{if } F(B) < F(P_t) \end{cases} \quad (8)$$

In conclusion, HHO controls the four types of hunting apparatuses among Harris Hawks and prey using energy E and factor u to get the best possible solution to the problem.

3.6.2. Improved Sine-Cosine and Cauchy joint HHO (SCHHO)

Because of structural flaws, the search process in conventional HHO frequently stalls out at the local optimum and thus provides only mediocre convergence accuracy. As a result, the HHO added to it in order to upsurge the variety of the Harris Hawk populace, speed up the search, and boost its search capabilities.

The global investigation step makes use of the function to broaden the Harris Hawk population, expand the search area, and improve the algorithm's capacity for discovering new information. Using the Cauchy operator, it takes full advantage of the mutation impact at both extremes of the function to find the global optimum solution. Cauchy's density function, as given in standard form,

$$f_t(P) = \frac{1}{\pi} \left(\frac{1}{P^2 + t^2} \right) \quad (9)$$

Harris Hawks will spend less time exploring the local interval and more time searching for the global optimum value following a Cauchy mutation since the highest charge of the Cauchy function is modest. The Harris Hawk is, therefore, free to leap past the local extreme point since the Cauchy function smoothly decreases from the sides following a Cauchy variation position update. The existing global optimal position P_{best} is revised using the Cauchy variation mathematical model as:

$$P_{\text{best}}^N = [0.6 \times P_{\text{best}}] + [0.4 \times P_{\text{best}} \times \text{Cauchy}(0,1)] \quad (10)$$

In the above equation, P_{best}^N is the updated global optimal position.

To enhance the capability of the local adaptive weight approach is used in the stage of local exploitation to update the neighborhood of prey location.

The expression for the modified prey location using adaptive gain G is

$$G = 0.5 \times \cos\left(\frac{\pi \times t}{2T}\right) + 0.5 \times \sin\left(\frac{\pi \times t}{2T}\right) + 1 \quad (11)$$

$$P_{\text{prey}}^N(t) = G \times P_{\text{prey}}(t) \quad (12)$$

where T is the total sum of possible repetitions, and t is the current iteration count.

Harris Hawks are opportunistic predators, and the location of their prey has a significant impact on the population as a whole. However, when the Harris Hawks' sought-after prey is discovered at the local ideal spot, a swarm of followers will quickly assemble there. The discoverer and the population as a whole will hit a plateau, leading to a decline in geographic variety and an increase in the likelihood of seeing a local extreme value. This issue is addressed by combining the SCA in the HHO location update and using SCHHO^[42] method as given by the following equations.

In SCHHO model implemented in this paper, there are two phases of optimization: discovery and use. These two steps get us closer and closer to the global ideal answer. Two-stage position update equations are given by:

$$P_{t+1} = P_t + a \times \sin(b) \times |c \cdot P_{\text{best}} - P_t|, d < 0.5 \quad (13)$$

$$P_{t+1} = P_t + a \times \cos(b) \times |c \cdot P_{\text{best}} - P_t|, d \geq 0.5 \quad (14)$$

In the above equation a, b, c, d are random statistics and make up the bulk of SCA in Equations (13) and (14). Harris Hawks' next course of action and the rate at which they go from exploring to exploiting are both under the command of a . Harris Hawks' range is set by the parameter b . When the position is updated using equations (13) and (14) based on value of d .

3.7. Networking unit

Data may be sent to the user through a GSM modem, and an enhanced EfficientNet technique is used for identification in every frame. The two examples of wireless networks that might be used to transmit a computer. To begin transmitting, a SIM card is required, as is a device. The wireless sensor network (WSN) gathers room

state data and sends it to the data storage for analysis of fire cause. When the GSM modem receives a signal from the microcontroller, it sends a short message service (SMS) to the rescue authorities to alert it and prompt it to take action^[43,44].

4. Results and discussion

Here, we demonstrate how well the DSRO augmentation based EfficientNet with SCHHO technique performs on the forest fire dataset for categorization. The software programs were run on an Anaconda installation of Python 3.7 using the Keras library. The results of this study’s performance analysis are presented below in the next sub-section.

4.1. Hyper-parameter selection

To determine the optimal settings for the various hyper-parameters, we conducted empirical tests. We tested 20 alternative choices for the starting learning rate, from 0.00001 to 0.1. We also put the model through its paces with 16, 32, 64, and 100-person batches. Extensive testing led to the hyper-parameters listed in **Table 2** being utilized for training in the simulation.

Table 2. Simulation parameters.

Parameters	Value
Loss purpose	Binary cross entropy
Extreme epochs	50
Epoch	100
Authentication frequency	100
Batch extent	64
Learning rate	0.01

4.2. Performance metrics

We measured how well the proposed model performed by calculating True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) metrics. In various research studies, equations (15)–(18) have been used to determine accuracy, recall, precision and F1-score parameters. In this paper for evaluating the performance of the proposed method, accuracy values were computed for the proposed method.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (15)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (16)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (17)$$

$$\text{F1score} = \frac{(2 \times \text{precision} \times \text{recall})}{(\text{precision} + \text{recall})} \quad (18)$$

In the following section we show the comparison of accuracy values obtained by using the proposed model with accuracy values obtained by using the other reference research models.

4.3. Comparative analysis of proposed model with existing procedures

In this analysis, the proposed method consisting of DSRO based enhanced EfficientNet using SCHHO is compared with the various existing techniques such as YOLOv4^[22–24,31], MS-FRCNN^[25], Grid RCNN^[26] and EfficientNet^[45], as shown in **Table 3**. The accuracy values of the proposed model and the various existing models considered for comparative analysis are depicted as percentages. **Figure 6** depicts the graphical analysis of the proposed model using accuracy in the form of bar chart.

Table 3. Comparative investigation of proposed technique with existing tactics.

Techniques	Accuracy
YOLOv4	81.9
Grid RCNN	83.9
MS-FRCNN	85.2
EfficientNet	85.3
Proposed Method	87.4

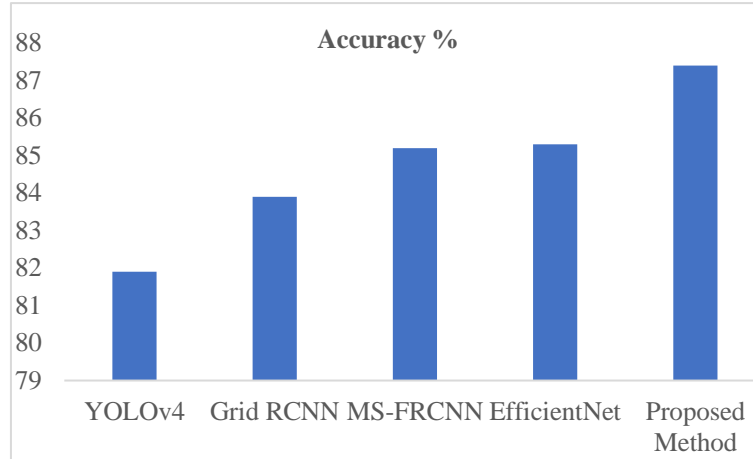


Figure 6. Graphical analysis of proposed model using accuracy.

When analyzing various parameters, according to the YOLOv4 technique, the accuracy was 81.9%. Then, using the Grid RCNN technique, the accuracy was 83.9%. According to the MS-FRCNN strategy, the accuracy score was 85.2%. Then, using the Efficient Net technique the accuracy was 85.3%. The proposed method used in this paper with DSRO augmentation based SCHHO-EfficientNet achieved the accuracy value of 87.4%. The proposed DSRO based SCHHO-EfficientNet method gives better accuracy than other existing methods, as implemented in this study, which highlights its ability to accurately identify forest fire occurrences.

4.4. Discussion and limitation

To prevent the model from becoming unstable due to early overfitting and to keep the distribution smooth during training, we employed the warmup and cosine learning rate learning techniques. When training with several tasks, you may either back propagate the loss for each task individually, or you can lose values for each task.

Nonetheless, there are still gaps in the investigation. First, because of the limited quantity of pixel information available, tiny target recognition poses significant basic challenges. From a data-neutral standpoint, the technique just enhances detection quality. Second, smoke is a typical early fire symptom, but the model does not account for it. Finally, due to the complexities of forest ecosystems, the model may be hampered by the problem of shade by covered plants, whereas conventional instruments like thermometers, humidity meters, infrared cameras, etc. remain unaffected. As a result, multi-sensor fusion can be a promising area for further research.

5. Conclusion and future work

In this paper, we developed a novel method for detecting forest fires with the use of artificial intelligence, IoT gadgets & sensors and the model's detection accuracy for tiny targets is considerably enhanced by DSRO augmentation and the enhanced detection efficiency of the enhanced EfficientNet with SCHHO model. The network's performance on forest fire detection is enhanced by the feature extraction module that is common to all three jobs. High accuracy ratings highlight the model's dependability. The experimental findings show

that the method provides better accuracy than existing methods and hence the proposed strategy is successful compared to other reference models for forest fire detection. The experimental findings showed an improvement of 5% in accuracy using the proposed method compared to the existing standard model for forest fire detection, and an improvement of 2% compared to EfficientNet model in detecting forest fire. The model is positioned as a viable and adaptable method for precise risk assessment in a variety of environmental circumstances. As a result, we think the approach may be utilized to successfully put a stop to the worsening global climate problem and the resulting number of casualties. Installed in woods, it can detect smoke and alert authorities to the precise position of any fires in the area, preventing them from spreading for days. Finally, we believe this technique has the potential to be used effectively to halt the spread of wildfires.

Future work

This research work has room for more development and optimization in future works, both in terms of hardware elements and software processes. Adopting duty cycling regulations might improve its categorization qualities and reduce its power consumption. To further enhance the DL models at the deployment location, the prototype may be outfitted with data-storing capabilities to capture a dataset using reinforcement learning paradigms. The study also plans to implement the approach on edge devices, with the goal of better detecting forest fires through multi-sensor fusion.

Author contributions

Conceptualization, VA, KK and AKS; methodology, VA, KK and AKS; software, NS and RJA; validation, NS and RJA; formal analysis, VA, KK and RJA; investigation, AKS and NS; resources, RJA; data curation, VA and RJA; writing—original draft preparation, VA, KK and AKS; writing—review and editing, VA, KK, AKS, NS and RJA; visualization, RJA; supervision, VA and RJA; project administration, VA; funding acquisition, RJA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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