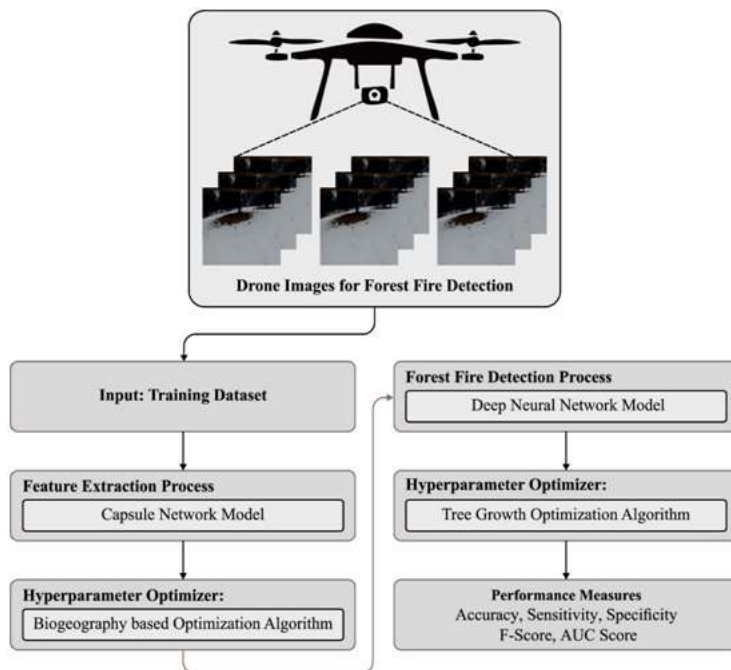


Exploiting Drone Images for Forest Fire Detection using Metaheuristics with Deep Learning Model

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GRAPHICAL ABSTRACT



Abstract

Forest fires are a global natural calamity causing significant economic damage and loss of lives. Professionals forecast that forest fires would raise in the future because of climate change. Early prediction and identification of fire spread would enhance firefighting and reduce affected zones. Several systems have been advanced to detect fire. In recent times, Unmanned Aerial Vehicles (UAVs) are used for tackling this issue

because of their ability, high flexibility, and their cheap price to cover vast areas during the nighttime or daytime. But still they are limited by difficulties like image degradation, small fire size, and background complexity. This study develops an automated Forest Fire Detection using Metaheuristics with Deep Learning (FFDMDL-DI) model. The presented FFDMDL-DI technique exploits the DL concepts on drone images to identify the occurrence of fire. To accomplish this, the FFDMDL-DI technique makes use of the Capsule Network (CapNet) model for feature extraction purposes with a biogeography-based optimization (BBO) algorithm-based hyperparameter optimizer. For accurate forest fire detection, the FFDMDL-DI technique uses a unified deep neural network (DNN) model. Finally, the tree growth optimization (TGO) technique is utilized for the parameter adjustment of the DNN method. To depict the enhanced detection efficiency of the FFDMDL-DI approach, a series of simulations were performed. The outcomes reported improvements in the FFDMDL-DI method over other DL models.

Keywords: Forest fire; Deep learning; Drone images; Transfer learning; Metaheuristics; Computer vision

1 Introduction

As everyone knows forests are a significant part of natural resources [1]. It can maintain biodiversity, purify the air, and provide habitat for animals popularly called the "Lung of the Earth", the forest has social economic, and rich natural values [2]. But the current ecological condition has made the chance of forest fires more frequent, causing large areas of forest loss annually. The California fire, which happened in November 2018, has exhibited the severe damage of forest fires once again [3, 4]. So, early prevention of forest fires is highly significant for protecting natural resources and people, and eventually, the rapid spread of wildfires and the long burning period is

avoided. With technological development, UAVs probably turn out to be the most effective tool for detecting forest fires in the early stage [5]. It has empowered a huge variety of applications namely land surveying, surveillance, mapping, and tracking. UAV-related systems aid with accurate fire management and render realtime data to reduce the damage from fires and their ability and cheap price would cover large zones either during the night or day for a long period [6]. The incorporation of UAV with infrared or visual sensors aids in identifying potential fires at both nighttime and daytime [7, 8]. Moreover, segmentation and fire detection has shown remarkable growth with the usage of deep learning (DL) approaches. DL-related fire identification approaches were utilized for identifying the colour of wildfire and its geometrical attributes namely height, angle, width, and shape [9]. Their outcomes were utilized as inputs to a fire propagation methods.

With the implementation of deep learning (DL) technology in domains of intelligent agriculture, logistics, and indoor target positioning, authors have also presented DL technology in identifying forest fires for enhancing the precision of wildfire detection by mining deep semantic features from images [10, 11]. To extract deep abstract features from imageries, it is essential to build a deep-level network method, and training deep neural networks (DNNs) was a complex and time-taking procedure [12]. Moreover, the deep model training demanded a lot of labelled instances. This turns out to be the bottleneck in forest fire detection depending on UAV imageries, and the occurrence of transfer learning (TL) technology offers an opportunity to overcome this issue [13, 14]. TL is just transmitting trained model to innovative task and understanding the modelling of the novel job by optimally tuning model parameters. If there were inadequate labelled instances [15], TL can solve issue of overfitting training caused by some labelled instances.

This study develops an automated Forest Fire Detection using Metaheuristics with Deep Learning (FFDMDL-DI) model. The presented FFDMDL-DI technique exploits

Capsule Network (CapNet) model for feature extraction purposes with a biogeography-based optimization (BBO) algorithm-based hyperparameter optimizer. For accurate forest fire detection, the FFDMDL-DI technique uses a unified deep neural network (DNN) model. Finally, the tree growth optimization (TGO) technique was utilized for the parameter adjustment of the DNN algorithm. To depict the enhanced detection efficiency of the FFDMDL-DI approach, a wide range of simulations were performed.

2 Literature Review

In [16], introduced a UAV image-related forest fire identification method. Initially, the SVM classifier and LBP feature extraction were utilized for smoke identification and for discriminating wildfire. To precisely detect wildfire in the initial stage, as per the CNN, it has features that reduce parameters and enhances the training efficiency using weight sharing, pooling, and local receptive domain. This study modelled another technique for identifying wildfires using CNNs. To insert the image into the CNN network, image preprocessing operations namely smooth low-pass filtering, and histogram equalization were executed earlier. Zhang et al. [17] present an FT-ResNet50 method related to TL. The technique migrates ResNet network trained on an ImageNet database and their initialized variables into targeted data of wildfire detection relies upon UAV images. Integrated with features of the targeted dataset, Adam and Mish's functions were utilized for optimal tuning of 3 convolutional blocks of ResNet, and network structure parameters and focal loss function were included for optimizing the ResNet network, for deriving deep semantic information effectively from fire imageries.

Rahman et al. [18] presented a forest fire identification technique relevant to a CNN structure employing a new fire detection database. Particularly, this technique even used separable convolutional layers (demanding fewer computing resources) for instant fire identification and convolutional layers. Almeida et al. [19] introduce a new lightweight CNN technique for forest fire identification utilizing RGB images. This technique grants more benefits compared to the other approaches used for similar tasks.

This CNN was employed with aerial images from video surveillance mechanisms and UAVs, integrated with edge computing gadgets for image processing including CNNs. The presented technique can send forest fire alerts. The images need not be transferred to a cloud computer since it is processed in an edge device.

In [20], the authors presented PDAM-STPNet (parallel spatial domain attention mechanism with a small-scale transformer featured pyramid method forest smoke identification network) related to Net by using YOLOX-L as a baseline. Initially, to improve the percentage of small wildfire smoke target in the database, the authors leverage component stitching data enhancement for generating small wildfire smoke targeted imageries in scaled collage. Afterwards, to completely derive the smoke texture features, the authors devised a PDAM for considering the global and local texture of smoke with symmetry. A DL fire identification method was presented in [21], pointing at enhancing the detection efficiency and accuracy through UAVs. A large-scale YOLOv3 network was advanced which safeguard accuracy of detection.

3 The Proposed Model

In this study, a new FFDMDL-DI approach was formulated for intelligent forest fire classification on drone images. The presented FFDMDL-DI method follows different stages of operations such as CapNet feature extraction, BBO-based hyperparameter tuning, unified DNN-based classification, and TGO-based parameter optimization. Fig. 1 defines the working procedure of the FFDMDL-DI system.

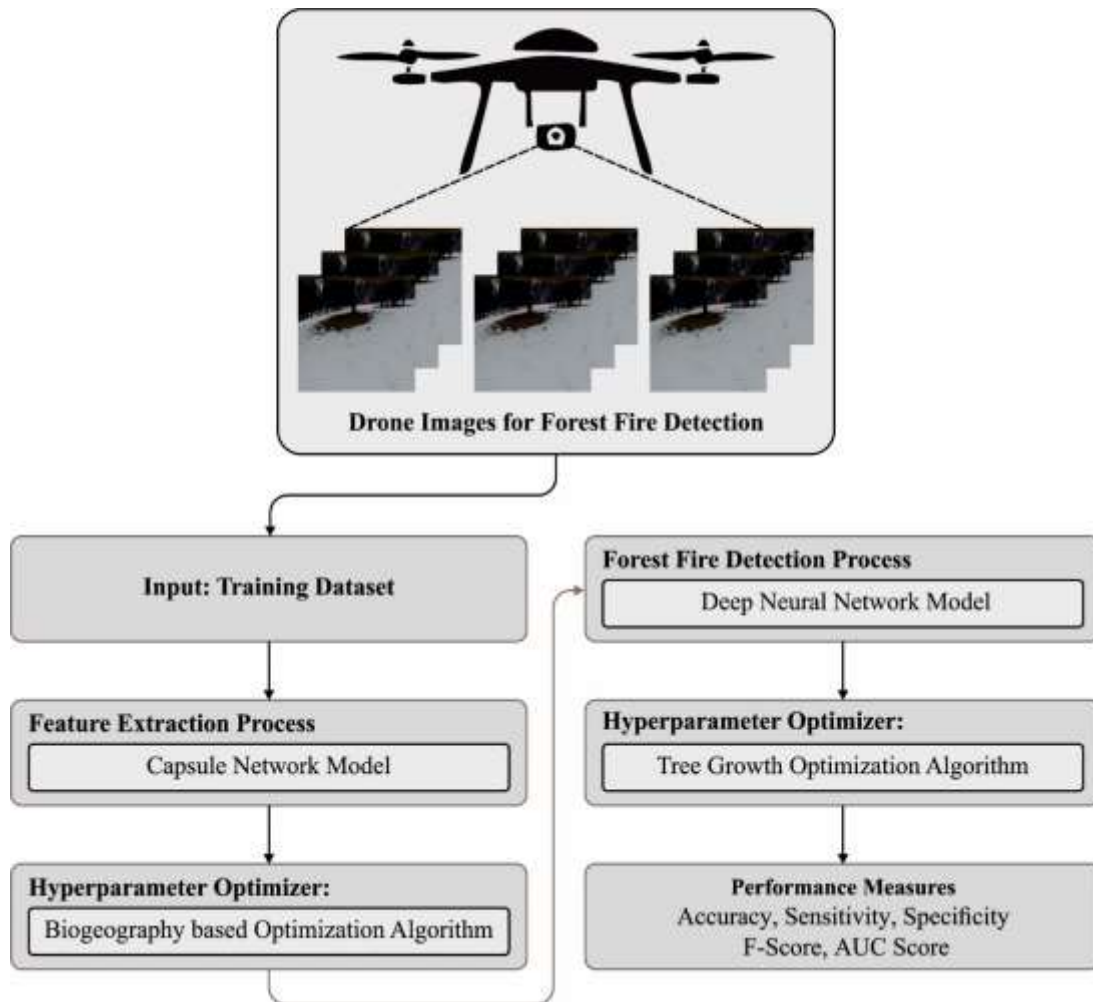


Figure 1: the Working process of FFDMDL-DI system

3.1 Feature Extraction Module

To produce feature vectors, the CapNet model is utilized in this work. CNN acts on image datasets and discovers features of an images to detect objects having information. In this work, the layer only detects the edge of the object, and deeper layers might discover complicated feature of the object [22]. The CNN-based DL algorithm mainly uses every learned feature for making concluding predictions. The main drawback of CNN is the lack of pooling function and spatial information. In the max pooling function, only essential data found from active neuron is to be collected to the next layer. Consequently, some significant spatial information will be lost between the layers. Thus,

to overcome these challenges of CNN, the study used a superior form of CovNet named Capsule Network or CapNet. CapNet is a kind of CNN. CapNet was introduced to address the hierarchical modelling problem and is better suited for these abovementioned problems. CapNet doesn't resemble the Pooling layer used in CovNet. Due to pooling in CovNet, it increases the speed of algorithmic runtime and reduces the details. But in CapNet, the pooling layer is considered minor detail which depends on CapNets (inverse rendering concept). The two essential functions of CapNet were Squashing and Routing algorithms. In the process of training, the activation vector of correct number was masked out and these activity vectors are applied to recreate input images with the aid of the FC decoder.

For optimal hyperparameter adjustment, the BBO algorithm is used here [23]. With that regard, each creature has its particular ecological value that was represented by the ecological suitability indicator, and also it illustrates degree of its quality or pleasure. The major aspect of biogeography-oriented optimizer, called BBO, was the acquisition of new features moving in opposite direction, from lower to higher, and the migration of characteristics from higher to lower. It is likely to arrive at the optimum answer by reiterating the process defined before. Migration and mutation are the two primary operators:

Migration: data might be transferred from one solution to another next via operator; but it depends on two parameters demonstrating the migration and movement rates as follows:

$$\lambda_k = \lambda_{\max} \left(1 - \frac{k}{k_{\max}} \right) \quad (1)$$

$$\mu_k = \mu_{\max} \left(\frac{k}{k_{\max}} \right) \quad (2)$$

Where μ_k and λ_k represent rates of emigration and immigration and k describes solution rank. Based on the abovementioned process, the rate of immigration and emigration were equivalent which has the highest amount of species (S_{\max}).

Mutation: illnesses or tragedies induce alteration in the coefficient of solution, the transformation concept might be viewed as unpredicted variation in species. The mutation value of species is expressed in the following:

$$m_k = m_{\max} \left(1 - \frac{P_k}{P_{\max}} \right) \quad (3)$$

In which the m_k and m_{\max} signify the mutation rates, P_k and P_{\max} represent every one of the species' probability, and k represents solution rank. The P_k is formulated by the following expression:

$$p_k = \begin{cases} -(\lambda_k + \mu_k)P_k + \mu_{k+1}P_{k+1} & k = 0 \\ -(\lambda_k + \mu_k)P_k + \lambda_{k-1}P_{k-1} + \mu_{k+1}P_{k+1} & 1 \leq k \leq k_{\max} - 1 \\ -(\lambda_k + \mu_k)P_k + \lambda_{k-1}P_{k-1} & k = k_{\max} \end{cases} \quad (4)$$

3.2 Fire Detection Module

In this study, the DNN method is used for the forest fire detection process. DNN was a large-scale non-linear system contains several neural cells similar to the human brain and has multiple hidden layers (HLs) among output and input layers. In DNN architecture, forward propagation was utilized for acquiring the output values, whereas backward propagation was utilized to improve the parameters of the model [24]. In this study, rich information is extracted in every HL and merged in the final HL through the new framework (a unified DNN with multilevel features). In this work, we have 6 layers (11-6-5-5-10-5) involving 4 HLs, one input, and output layers. Unlike HL has abstract features in various levels and merges them in final HL for classification to optimize the performance of the classifier. The 11 feature which is extracted was devised in Section 2 were regularized. The feature was contributed towards input layer and later transferred to HL 1 by the forward propagation method. Every neuron in next layer is based on its preceding layer and is computed by using Eqs. (5) and (6). Specifically, the purple neuron of HL 4 is evaluated by using Eqs. (5) and (7), and red neurons of HL 4 are evaluated by using Eqs. (5) and (8). Although the neuron in HL 1 propagates to HL 2, at the same time, the neuron from HL 1 propagates directly toward

HL 4. Likewise, neurons in HL 2 transmit to HL 3 and 4. In the final HL, 10 neurons with 3 levels are fused to comprehensively forecast type of weld defect. The neuron of output layer ranges from zero to one, the highest of which signifies hypothesis of weld defect type: slag inclusion (SL), porosity (PO), lack of fusion (LF), crack (CR), and lack of penetration (LP). The deep neural architecture uses multilevel features derived from the HL combined to categorize weld defects precisely.

$$a_j^{(l+1)} = g\left(\sum_i z_{ij} + b_j^{(l+1)}\right) \quad (5)$$

$$z_{ij} = a_i^{(l)} w_{ij}^{(l,l+1)} \quad (6)$$

Where $a_j^{(l)}$ refers to j-th neuron of l-th layers, $g(x)$ shows the activation function, $w_{ij}^{(l,l+1)}$ indicates the weight and $b_j^{(l+1)}$ represents bias between l-th and (l + 1)th layers.

To compute the purple neuron of HL 4, Eq. (6) must be substituted with Eq. (7). Likewise, to compute the red neuron of HL 4, Eq. (6) must be substituted with Eq. (8).

$$z_{ij} = a_i^{(l-2)} w_{ij}^{(l-2,l+1)} \quad (7)$$

$$z_{ij} = a_i^{(l-1)} w_{ij}^{(l-1,l+1)} \quad (8)$$

DNN is frequently trained with the BP model which creates a better sample of an effective gradient-related learning mechanism. In this study, a special DL architecture with a forward propagation model has been proposed and trained with the BP model. Initially, we define cost function for the unified DNN with normalization term, and it was provided as Eq. (9). Next, initialize the model parameter and execute a few pretrained, next, the backpropagation algorithm has been implemented for computing the gradient for cost function of DNN. Then, the gradient descent algorithm is used for minimizing cost function. Then, upgrade model parameters by using Eqs. (10) and (11), next calculate gradient again for minimizing the cost function until convergence.

$$J(W_t b) = \frac{1}{2m} \sum_{i=1}^m \sum_{k=1}^k [(h_{\theta}(x^i))_k - y_k^{(i)}]^2 + \frac{\lambda}{2m} \sum_l \|\omega\|_2^2 \quad (9)$$

In Eq. (9), $J(W, b)$ indicate the loss, m represents the number of training sets, k shows number of kinds of weld defects, x^i implies inputted feature of i -th training instance, $(h_\theta(x^i))_k$ shows the k -th neurons of output layer that can be a hypothesis for input x^i , $y_k^{(i)}$ represent the i -th elements of label y_k , λ denotes the regularization factor, W represents weighted matrix, ω indicates weighted vector for all the layers, b denotes the bias vector, l signifies a layer of the method.

$$\omega \rightarrow \omega - \alpha \frac{\partial J}{\partial \omega} \quad (10)$$

$$b \rightarrow b - \alpha \frac{\partial J}{\partial b} \quad (11)$$

Where α refers to learning rate.

Finally, the TGO technique is used for the parameter adjustment of the DNN model. The TGO is a meta-heuristic technique simulated in the development design and survival drive of trees from the jungles [25]. To optimize the viewpoint, the trees can be analogous to solution, and its development signifies fitness function (FF). The TGO mechanism by separating the tree (solution) into 4 groups. During the primary group, it is higher trees with favourable situations to develop and ample accessibility to sunlight. The rate of growth of the group one trees has slower and it can be older than other trees. The competition among group one tree has merely for food. The trees under the secondary group compete for food and sunlight. For obtaining maximal sunlight, such trees move nearby the 2 neighbouring sunlight-getting trees. During the tertiary group, the trees can be both eliminated and replaced based on their underachievement. The group 4 trees were novel plants which are nearby the group one trees, therefore it can be a superior rate of growth because of the appropriate environment. The next steps can be monitored to choose features utilizing the TGO:

a) Primarily, a population was created arbitrarily with an entire of N trees (solutions). To whole created populations, the fitness value was estimated. The trees can be arranged based on their fitness value from the ascending order. In the arranged trees,

a primary group was generated with an N_1 count of trees. The tree in primary group can be upgraded with a swapping function. An optimum tree (global optimum solution) can be preserved for the next generation.

b) Afterward, the N_2 count of trees can be preserved to develop of secondary group. As noted previously, the trees under the secondary group search for sunlight by searching nearby 2 trees,

$$D_{trees} = \sqrt{(\sum_{i=1}^{N_1+N_2} (P_{N_2}^t - P_i^t)^2)} \quad (12)$$

The current position and an i^{th} tree was defined by P_{N_2} and P_i correspondingly. The P_{N_2} strides with the procedure of cross-over and mutation.

c) Based on fitness values, the underachieving trees from tertiary groups were both eliminated and replaced by novel ones. Therefore, an entire count of trees from the 3 equivalent groups

$$N_3 = N - (N_1 + N_2) \quad (13)$$

d) During the fourth phase, a novel N_4 count of trees can be created nearby optimum trees (group one) utilizing a masking procedure. These group 4 trees (entire N_4) are later than the whole population. The stages a) to d) can be repeated still more enhancements from the optimum solution halt. The optimum tree (solution) in group one was then chosen as the global optimum that defines the optimum feature subset.

The fitness selection becomes a vital component of the TGO method. It can be used to evaluate the aptitude (goodness) of candidate solutions [26]. Nowadays, accuracy value will be the main condition used to devise a fitness function.

$$Fitness = \max(P) \quad (14)$$

$$P = \frac{TP}{TP+FP} \quad (15)$$

From the expression, TP signifies true positive, and FP designates false positive value.

4 Results and Discussion

The experimental study of the FFDMDL-DI method is performed on the FLAME dataset [27], which contains 6000 samples as depicted in Table 1. Fig. 2 shows the sample fire and no-fire images.

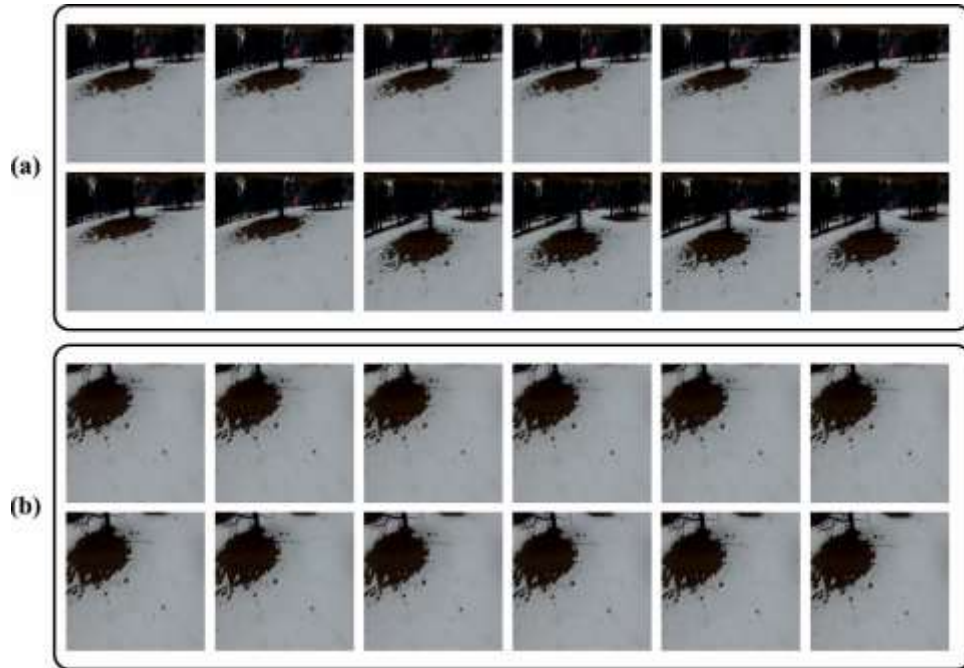


Figure 2: a) Fire b) No-Fire Images

Table 1: Details of the dataset

Class	No. of Samples
Fire	3000
No-Fire	3000
Total Number of Samples	6000



Figure 3: Confusion matrices of FFDMDL-DI technique (a-b) TRS/TSS of 80:20 and (c-d) TRS /TSS of 70:30

The fire detection performance of the FFDMDL-DI model under varying sizes of datasets is reported in Fig. 3. On 80% of the TRS database, the FFDMDL-DI model has identified 2407 fire samples and 2368 no-fire samples. At last, on 20% of the TS database, the FFDMDL-DI method identified 580 fire samples and 617 no-fire samples.

Meanwhile, on 70% of the TRS, the FFDMDL-DI technique has identified 2061 fire samples and 2036 no-fire samples.

An average fire detection results of the FFDMDL-DI model under fire and no-fire cases with 80:20 of TRS/TSS is given in Table 2 and Fig. 4. On 80% of the TR database, the FFDMDL-DI technique has reached the average $accu_{bal}$ of 99.48%, $sens_y$ of 99.48%, $spec_y$ of 99.48%, F_{score} of 99.48%, and AUC_{score} of 99.48%. Meanwhile, on 20% of the TS database, the FFDMDL-DI method has reached an average $accu_{bal}$ of 99.76%, $sens_y$ of 99.76%, $spec_y$ of 99.76%, F_{score} of 99.75%, and AUC_{score} of 99.76%.

Table 2: Fire detection outcome of FFDMDL-DI system on 80:20 of TRS/TSS

Class	Accuracy _{bal}	Sensitivity	Specificity	F-Score	AUC Score
Training Phase (80%)					
Fire	99.46	99.46	99.50	99.48	99.48
No-Fire	99.50	99.50	99.46	99.47	99.48
Average	99.48	99.48	99.48	99.48	99.48
Testing Phase (20%)					
Fire	100.00	100.00	99.52	99.74	99.76
No-Fire	99.52	99.52	100.00	99.76	99.76
Average	99.76	99.76	99.76	99.75	99.76

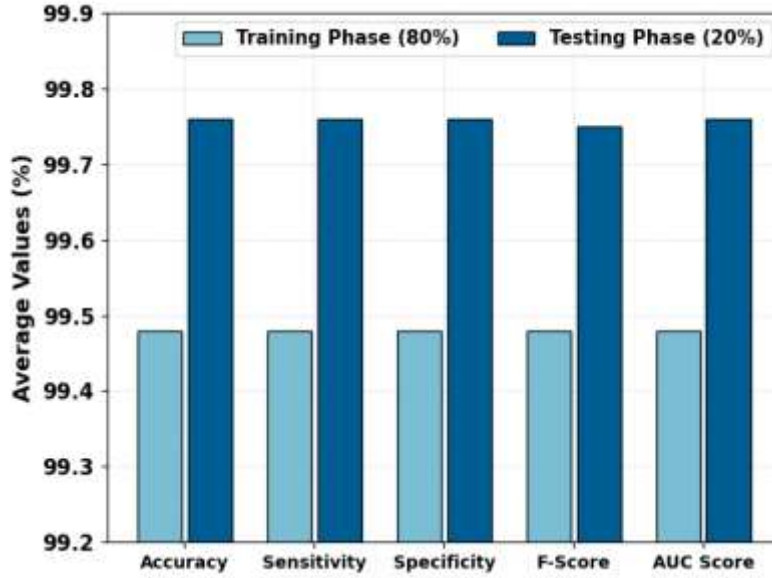


Figure 4: Average outcome of FFDMDL-DI system on 80:20 of TRS/TSS

An average fire detection results of the FFDMDL-DI model under fire and no-fire cases with 80:20 of TRS/TSS is given in Table 3 and Fig. 5. On 70% of TR database, the FFDMDL-DI approach has achieved an average $accu_{bal}$ of 97.55%, $sens_y$ of 97.55%, $spec_y$ of 97.55%, F_{score} of 97.55%, and AUC_{score} of 97.55%. Eventually, on 30% of the TS database, the FFDMDL-DI method has achieved an average $accu_{bal}$ of 98.39%, $sens_y$ of 98.39%, $spec_y$ of 98.39%, F_{score} of 98.39%, and AUC_{score} of 98.39%.

Table 3: Fire detection outcome of FFDMDL-DI approach on 70:30 of TRS/TSS

Class	Accuracy _{bal}	Sensitivity	Specificity	F-Score	AUC Score
Training Phase (70%)					
Fire	97.59	97.59	97.51	97.56	97.55
No-Fire	97.51	97.51	97.59	97.53	97.55
Average	97.55	97.55	97.55	97.55	97.55
Testing Phase (30%)					

Fire	98.20	98.20	98.57	98.36	98.39
No-Fire	98.57	98.57	98.20	98.41	98.39
Average	98.39	98.39	98.39	98.39	98.39

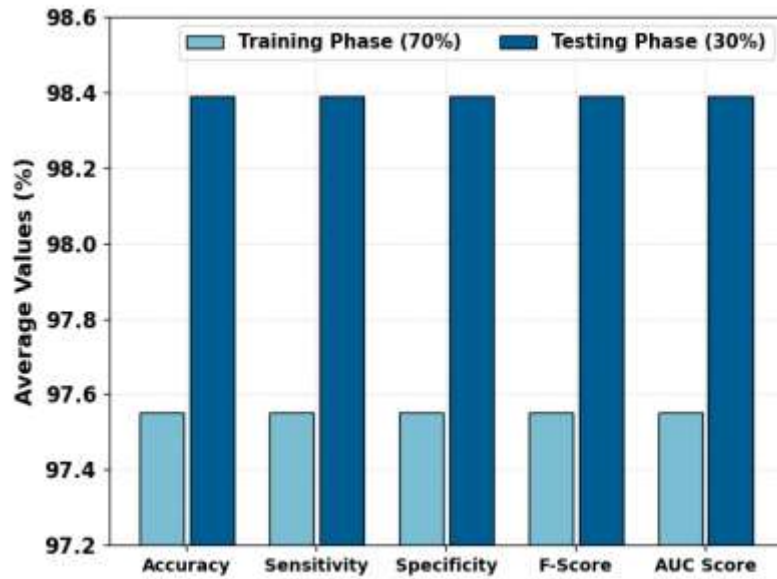


Figure 5: Average outcome of FFDMDL-DI system on 70:30 of TRS/TSS



Figure 6: TACY and VACY analysis of FFDMDL-DI system

The TACY and VACY of the FFDMDL-DI method are scrutinized on fire detection performance in Fig. 6. The outcomes show that the FFDMDL-DI approach has improvized performance with higher values of TACY and VACY. Seemingly, the FFDMDL-DI method has higher TACY outcomes.

The TLS and VLS of the FFDMDL-DI technique are tested on fire detection performance in Fig. 7. The figure exhibited that the FFDMDL-DI approach has revealed better performance with the minimal values of TLOS and VLOS. Notably, the FFDMDL-DI technique has minimal VLOS outcomes.



Figure 7: TLOS and VLOS analysis of FFDMDL-DI system

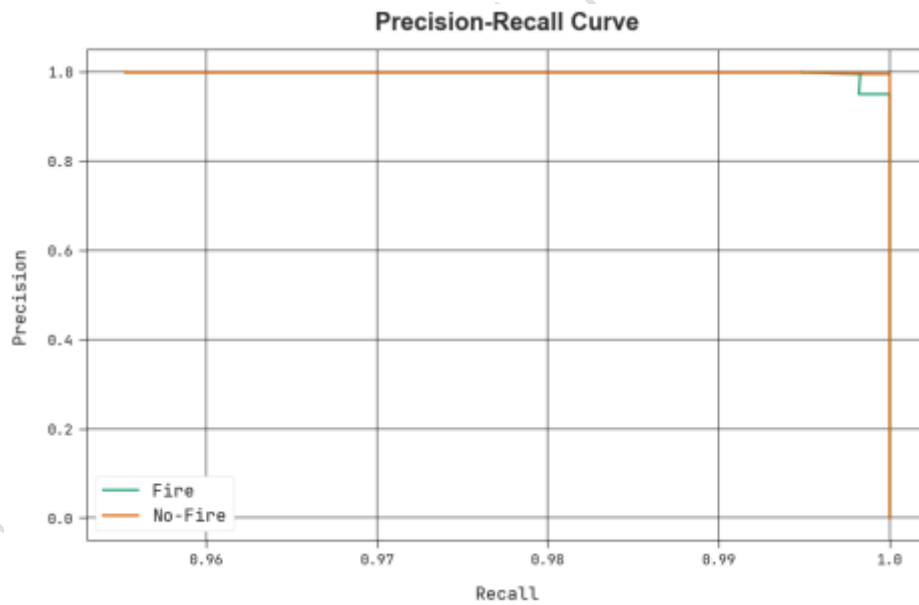


Figure 8: Precision-recall analysis of FFDMDL-DI system

A clear precision-recall review of the FFDMDL-DI system under the test database is given in Fig. 8. The outcomes show the FFDMDL-DI technique has improved enhanced values precision-recall values under every class.

In Table 4, detailed fire detection outcomes of the FFDMDL-DI method with recent methods are provided [17].

Table 4: Comparative analysis of FFDMDL-DI approach with other systems

Methods	Accurac y	Sensitivit y	Specificit y	F-Score
FFDMDL-DI	99.76	99.76	99.76	99.75
ResNet50	89.98	90.28	92.35	90.28
VGG16	91.14	91.45	94.21	91.14
Inception	92.51	93.73	96.52	92.60
KELM	94.55	95.18	98.56	95.07
LSTM	95.54	96.89	97.62	96.57

A comparative study of the FFDMDL-DI method in terms of $accu_y$ and F_{score} is represented in Fig. 9. The outcomes displayed that the FFDMDL-DI algorithm has shown improved results. Based on $accu_y$, the FFDMDL-DI model has achieved an increased $accu_y$ of 99.76% while the ResNet50, VGG16, Inception, KELM, and LSTM models have obtained reduced $accu_y$ of 89.98%, 91.14%, 92.51%, 94.55%, and 95.54% respectively. Moreover, based on F_{score} , the FFDMDL-DI method has attained an increased F_{score} of 99.75% while the ResNet50, VGG16, Inception, KELM, and LSTM approaches have gained a reduced F_{score} of 90.28%, 91.14%, 92.60%, 95.07%, and 96.57% correspondingly.

The brief study of the FFDMDL-DI algorithm interms of $sens_y$ and $spec_y$ is given in Fig. 10. The figure shown the FFDMDL-DI approach has shown enhanced results. Based on $sens_y$, the FFDMDL-DI technique has achieved an increased $sens_y$ of 99.76% while the ResNet50, VGG16, Inception, KELM, and LSTM approaches have gained

reduced $sens_y$ of 90.28%, 91.45%, 93.73%, 95.18%, and 96.89% correspondingly. Additionally, based on $spec_y$, the FFDMDL-DI method has attained an increased $spec_y$ of 99.76% while the ResNet50, VGG16, Inception, KELM, and LSTM techniques have attained reduced $spec_y$ of 92.35%, 94.21%, 96.52%, 98.56%, and 97.62% correspondingly. These outcomes showcased the enhanced results of the FFDMDL-DI model.

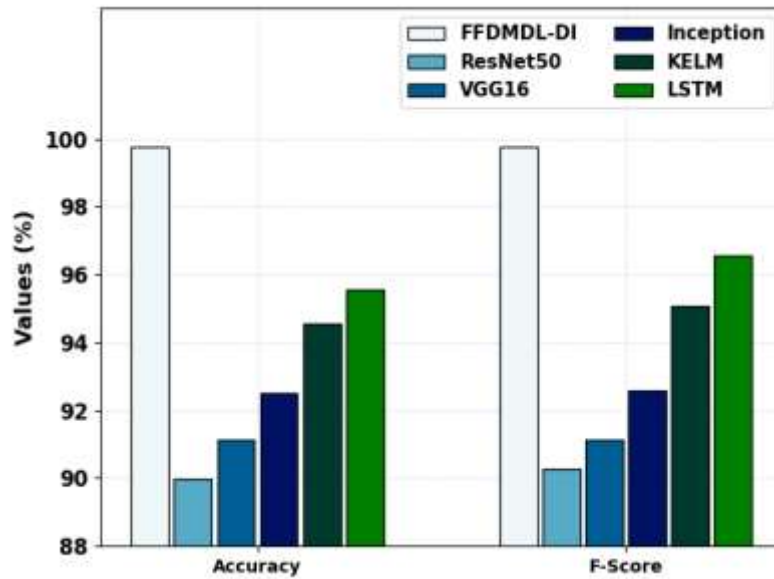


Figure 9: $Accu_y$ and F_{score} analysis of FFDMDL-DI approach with other systems

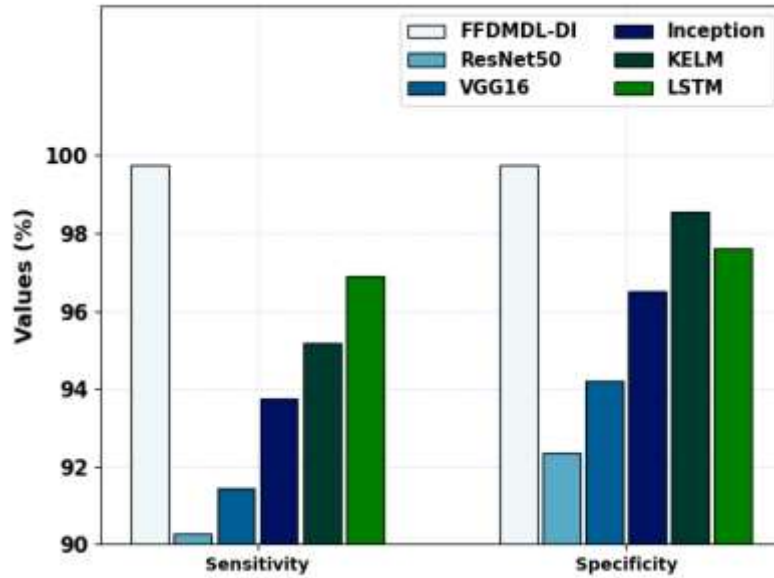


Figure 10: $Sens_y$ and $Spec_y$ analysis of FFDMDL-DI methodology with other techniques

5 Conclusion

In this study, a new FFDMDL-DI algorithm was formulated for intelligent forest fire classification on drone images. The presented FFDMDL-DI technique follows different stages of operations such as CapNet feature extraction, BBO-based hyperparameter tuning, unified DNN-based classification, and TGO-based parameter optimization. The presented FFDMDL-DI technique exploits the DL concepts on drone images to identify the occurrence of fire. For accurate forest fire detection, the FFDMDL-DI technique uses a unified DNN method. Finally, the TGO approach is used for the parameter adjustment of the DNN method. To depict the enhanced detection efficiency of the FFDMDL-DI algorithm, a sequence of simulations were effectuated. The outcomes stated the improvements of the FFDMDL-DI approach over other DL models. The detection performance of the FFDMDL-DI algorithm can be improved by hybrid metaheuristic algorithms in future.

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