DRONE IMAGERY FOREST FIRE DETECTION AND CLASSIFICATION USING MODIFIED DEEP LEARNING MODEL

by

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With the progression of information technologies, unmanned aerial vehicles (UAV) or drones are more significant in remote monitoring the environment. One main application of UAV technology relevant to nature monitoring is monitoring wild animals. Among several natural disasters, Wildfires are one of the deadliest and cause damage to millions of hectares of forest lands or resources which threatens the lives of animals and people. Drones present novel features and convenience which include rapid deployment, adjustable and wider viewpoints, less human intervention, and high maneuverability. With the effective enforcement of deep learning in many applications, it is used in the domain of forest fire recognition for enhancing the accuracy of forest fire detection through extraction of deep semantic features from images. This article concentrates on the design of the drone imagery forest fire detection and classification using modified deep learning (DIFFDC-MDL) model. The presented DIFFDC-MDL model aims in the detection and classification of forest fire in drone imagery. To accomplish this, the presented DIFFDC-MDL model designs a modified MobileNet-v2 model to generate feature vectors. For forest fire classification, a simple recurrent unit model is applied in this study. In order to further improve the classification outcomes, shuffled frog leap algorithm is used. The simulation outcome analysis of the DIFFDC-MDL system was tested utilizing a database comprising fire and non-fire samples. The extensive comparison study referred that the improvements of the DIFFDC-MDL system over other recent algorithms.

Keywords: *forest fire, computer vision, drone imagery, deep learning, metaheuristics, machine learning*

Introduction

An UAV, otherwise called a drone, is a flying device that is managed by one operator or by separately functioning onboard mechanisms. The UAV take on-demand image in low-flying planes for several reasons, which include visual surveillance, emergency product

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deliveries, accident rescue, population protection, and border enforcement [1]. The outlook of market expansion to vision processing within commercial aerial vehicles or UAV rises the overall number of vehicles. Additionally, few governments cheer up current drone persons to upgrade their gear to enhanced computation. In recent times, few nation's legal enforcement organizations enforced numerous recommendations for flying UAV in a regulated manner assuring it could not trespass on privacy of individual [2]. The increasing utility of drones in several applications which includes visual surveillance, recovered, and entertaining was accompanied by desired to securities [3].

With the rapid advances of society, novel necessities for the ecosystem were presented. Fire hazard that is one among the eight major natural calamities, spreads rapidly, is hard to control, and results in irreparable damages [4]. Thus, fire could often harshly deteriorate the environment and could even threaten the safety of life and property. Forest fires are common in major parts of the world and could cause substantial ecological damage [5]. The hot, dry conditions needed for a fire to start could even cause it to spread quickly, destroying trees, houses, and other structures. A smoke of fire and heat is harmful to animals and humans. Forest fires began with various elements like arsonists or careless campers, lightning. Fighting a forest fire often includes a greater number of people and agencies, forestry workers, firefighters, and police [6]. Detecting forest fires becomes a significant task to protect forests and prevent loss of human life and property. Deep learning (DL) and drones are capable to rise the accuracy and speed of forest fire detection (FFD). The DL method is trained for detecting forest fire characteristics in aerial images. The UAV could offer more accurate and frequent images of the forest canopy than ground-related images [7].

The current forest fire monitoring techniques include satellite remote sensing, artificial patrol, and observation towers, each of which has certain disadvantages and advantages [8]. The manual patrol observation technique would choose the patrol way, may go deep as to forestry region, and has sturdy mobility, but it seems hard to observe a blind region by utilizing this technique because of the greater influence of minimal efficiency, topography, and narrow vision domain [9]. The tower video observing technique could monitor large forests in realtime by using video observation apparatus and telescopes, but there was a blind region in an understory atmosphere in zones with a lack of mobility and dense trees [10]. The satellite remote sensing monitor technique is a higher positioning accurateness, extensive detection range, and could offer all-weather monitoring, but it is costly, it could detect only regions with a large fire, and fires could not be detected precisely in misty weather circumstances.

This article concentrates develops a new DIFFDC-MDL model. The presented DIFFDC-MDL model employs a modified MobileNet-v2 model to generate feature vectors. For forest fire classification, a simple recurrent unit (SRU) model is applied in this study. In order to further improve the classification outcomes, shuffled frog leap algorithm (SFLA) is used. The simulation outcome analysis of the DIFFDC-MDL approach was tested utilizing a database comprising fire and non-fire samples.

Literature review

Jiao *et al*. [11] devise a FFD method by using YOLO-v3 for drone-related aerial images. At first, a drone platform for the sake of FFD was formulated. Then according to the accessible computatational power of onboard hardwares, small-scale CNN were enforced by using YOLO-v3. In [12], the author addresses this method with natural resource management use-case but earlier forest-fire recognition by utilizing the famous CNN-related inference techniques was deemed in the UAV, which results in resource exhaustion. The author presents a lightweight hierarchical AI structure, which adaptively switches betwixt an advanced DL-based CNN method and a simple ML-related method. A DL fire detection method was modelled in [13], aims to improve the efficiency and detection accuracy through drones. A large-scale YOLOv3 network was primarily advanced which could assure the recognition accuracy. The method was then implemented on UAV-FFD, in which the fire images are capture by drone and sent to the ground-station from the realtime.

Rahman *et al*. [14] modelled an FFD technique related to a CNN architecture utilizing a novel fire detection dataset. Notably, this technique even leverges separable convolution layers (demanding fewer computing resources) for typical convolution layers and immediate fire detection. Hossain *et al*. [15] introduce a new technique that detects both smoke and flame from a single image utilizing a single ANN, block-related color features, and texture features). Such a technique can provide continuous, reliable, and rapid detection in any conditions and is merged into the prevailing drone related fire monitoring mechanism.

Zhang *et al*. [16] devises a FT-ResNet50 method depends on transfer learning (TL). The method migrates the ResNet trained on ImageNet database and its initializing variables into the targeted data of FFD related to drone images. Adam and Mish operations were utilized for fine tuning the three convolutional blocks of ResNet, and focal loss function integrated with the features of the targeted dataset, and network structure parameters were included for optimizing the ResNet network, for extracting very effective deep semantic data from fire images. In [17], a drone image-related FFD method was modelled. Initially, the SVM classifier and the LBP feature extraction were employed for smoke detection, thereby making preliminary discrimination of forest fires. In order to precisely detect from the prior stage of fires, in accordance with the CNN, it contains the features of minimizing the count of variables and enhancing the trained efficiency via local receptive field, pooling, and weight sharing.

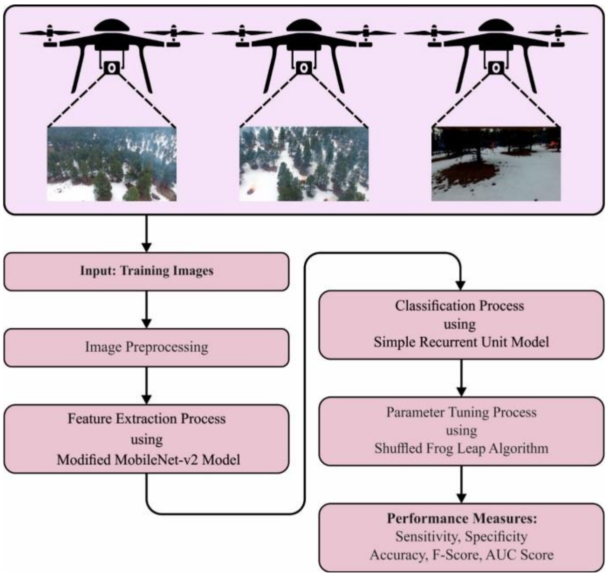

Figure 1. Overall block diagram of DIFFDC-MDL model

The proposed podel

In this article, a new DIFFDC-MDL system was introduced for forest fire classification in drone images. To accomplish this, the presented DIFFDC-MDL model designs a modified MobileNet-v2 model to generate feature vectors. For forest fire classification, the SFLA with SRU model is applied in this study. Figure 1 depicts the overall block diagram of DIFFDC-MDL system.

Modified MobileNet-v2 feature extraction

In the presented DIFFDC-MDL model, the modified MobileNet-v2 model is applied to generate feature vectors. MobileNetV2 is a deep CNN architecture intended for resource-constrained and portable situations [18]. This algorithm is based on inverse residual structure, where they are connected to bottleneck layer. The inspiration behind utilizing the MobileNetV2 network has lower latency, decreased parameter number, small size, and faster performance. We suggested a hybrid LSTM-RNN incorporated with reworked MobileNetV2 as a unique solution to inverse problem related to the brain tumor, (as a base model). The hybrid mechanism needs to evaluate the system parameter while modelling distinct grades of tumor, considering tumor mass simulation produced by titrating the angiogenesis, rate of proliferation, and concentration-driven motility, along with distinct aspects related to the radiological and pathological characteristics. The algorithm should detect variations in parameters of the model.

Firstly, it can be altered the MobileNetV2 model with an entirely different convolution layer that consists of malignant and benign non -meningioma and meningioma classes. This class is known as target labels. Next, TL is used for transferring the knowledge in original to target networks for acquiring a novel CNN architecture. Then, the study uses TL for training the finetuned network to extract features in GAP layers for classifier purposes that are additionally utilized for helping the LSTM. It provides a labeled matrix with the value for different ridge lines and picture areas that assist to tumor recognition. The key benefit of RNN modelling is that the LSTM recall dependency inside the sequences for establishing the group of PDE that cancer was categorized by, thus enhancing the result of model. The value of neurons in layers and the mean center initializing were dependent completely on classifying the tumour via the RNN technique, the LSTM spatiotemporal parameter aids the system to recognize hidden outlines in distinct frame-to-frame series. The hybrid mechanism splits the images into dynamic zone. The RNN network with TL has the considerable advantage of requiring lesser input dataset when generating remarkable outcomes. The altered MobileNetV2 based CNN architecture is retrained by dataset using TL based feature extraction. The source domain ζ_s can be described:

$$\zeta_s = \left\{ \left(m_1^s n_1^s \right), \ldots, \left(m_j^s, n_j^s \right), \ldots, \left(m_z^s, n_z^s \right) \right\} \tag{1}$$

The learning task is $L_s,\ L_\zeta,\ m_x^s,\ n_x^s \in \varphi$

The target domain ζ_t can be described:

$$\zeta_t = \left\{ \left(m_1^t, n_1^t \right), \ldots, \left(m_j^t, n_j^t \right), \ldots, \left(m_y^t, n_y^t \right) \right\} \tag{2}$$

The learning task is $L_t,\ m_y^t,\ n_y^t \in \varphi; \left(x, y \right)$ represent the training size dataset, whereas $y \ll x,\ n_j^s$, and m_j^t denotes the label for trained dataset. The pretrained model is trained on the target data based on the specification.

Forest fire detection and classification

In this study, the SRU model is applied for forest fire classification. The SRU is the simplest form of recurrent unit that is utilized to construct RNN [19, 20]. It accomplishes promising outcomes in time series application owing to thier internal memory ability. It take no gates and functions via multiplying x_t input vector by W_h weighted matrix and multiply the preceding output vector h_{t-1}that hold data from preceding unit through the weight matrixes U_h. Next, they are collectively added and passed over tan*h* activation function to convey an outcome value amongst 1 and –l. Figure 2 illustrates the infrastructure of SRU:

$$h_t = \sigma_h \left(W_h x_t + U_h h_{t-1} + b_h \right) \tag{3}$$

$$o_t = \sigma_o \left(W_o h_t + b_o \right) \tag{4}$$

where x_t is the input vector, h_t characterizes the hidden unit, o_t embodies the output vector, b_h and b_o refers to the bias vector of hidden and outcome vectors, W_h and W_o indicates the weight matrix of hidden and outcome vectors, and σ_h and σ_o denotes the activation function of hidden as well as outcome vectorss:

$$\sigma(x) = \tan h(x) = \frac{2}{1+e^{-2x}} - 1 \tag{5}$$

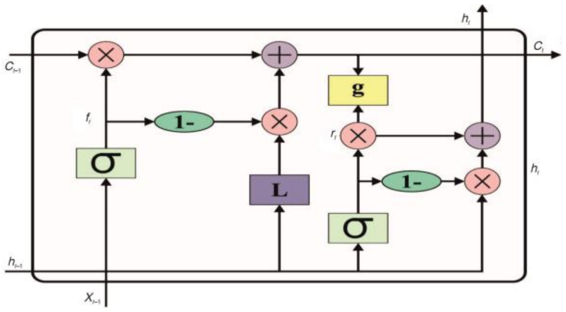

Figure 2. Structure of SRU

In order to further improve the classification outcomes, the SFLA is used for hyperparameter tuning. The optimized algorithm of SFLA mimics the foraging method of frog population [21]. The whole frog population is classified as to various memeplexes. The individual in all the memeplexes might interchange the data they have gathered and slowly get closer to the food resource in leadership of optimum individual in its own ethnic groups. Finally, subpopulation has completed the abovementioned operation, every individual would have regrouped to implement the shuffling process. Concisely, afterward, the population was initialized at random from solution spaces, the model comprises three major parts, viz., modal mixing shuffle, sub-population division, and local search.

Population division

The model could rank the fitness, *f*(/) of every individual *U*(/) in the extant population assessed through the fitness function (FF), and based on the sorting outcomes, the whole population is separated into *m* subpopulation M_1, M_2, …, M_m. There exist *n* frogs in all the subpopulations, and it is assured that = $m^* n$. Certain grouping rules are described:

$$\begin{gathered} M_k = [U(j)^k, f(j)^k \mid U(j)^k = U\left[k+m(\mathrm{j}-1)\right] \\ f(j)^k = f\left(k+m(j-1)\right), j = 1n, \ k = 1,\ldots,m \end{gathered} \tag{6}$$

Local search

Afterward, the grouping is performed, each memeplex carries out local search same as the location updating model in PSO, and the individual location with the poorest result in the memeplex is upgraded:

$$X_w^{'} = X_W + rand^{*}\left(X_b - X_W\right) \tag{7}$$

where X_b and X_W correspondingly characterize the local optimum solution and the worse solution in the existing sub-population and *rand* generates a random integer among zero and one. Once the novel individual $X_W^{'}$ has best performance when compared to the original individual X_W then X_W is substituted with $X_W^{'}$. Or else, the present global optimum solution replaces X_b in eq. (7) for regenerating a novel individual, and once this novel individual has no way for implementing superior to $X_{W,}$ then a novel individual location is produced at random in the solution space to substitute $X_{W.}$ Meanwhile, the location updating of worse individual often attains data in local/global optima, the entire population could rapidly lean toward the potential optimum solution location afterward the abovementioned evolutionary method continuously takes place.

Memeplexes shuffled

The SFLA absorb the concept of SCE approach, and then, memeplex completes the evolution, they are shuffled again for sharing the efficient data of separate population. Moreover, the FF values of all the populations are re-ranked, and the global optima individual is chosen.

The aforementioned procedure is reiterated still the ending criteria are fulfilled, then the data regarding the global optimum individual found could be outcome. The comprehensive pseudocode has been discussed in Algorithm 1.

Algorithm 1. The pseudo-code of SFLA

```
Initialization of population size N and the maximal amount of iterations T ;
      Arbitrarily initializing the population location data X from the solution space;
Evaluate the fitness of all the individuals and chose the optimum fitness values as X_b;
while t < T
      Sort fitness and split population as to memeplex based on the sorting outcomes;
      while im < m
            while (iN < N)
                  Define X_b and X_W, and set the fitness as f_b and f_w;
                  Upgrade the location of the worst individual X'_w in m- th memeplexes
                  based  on the Eq. (2);
                  Evaluate the fitness to a novel position of worst frogs as f_new;
                  If fnew < f_W
                        X_w = X'_w;
      else
                        Produce a novel solution at random in the potential domain;
                  endif
           endwhile
      endwhile
      Collect memeplex and shuffle the populations;
endwhile
return X_b;
```

The SFLA approach derives a FF for accomplishing better performance of the classifier. It solves a positive integer to characterize the improved accuracy of the candidate solutions. The minimized of the classifier error rate is supposed that FF:

$$\begin{aligned}\text{fitness}\left(x_i\right) &= \text{ClassifierErrorRate}\left(x_i\right)\\ &= \frac{\text{No. of misclassified instances}}{\text{Total No. of instances}}\times 100\end{aligned} \tag{8}$$

Table 1 Details on dataset

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

Results and discussion

In this section, the fire detection outcomes of the DIFFDC-MDL model are validated on the FLAME dataset [22]. It comprises 6000 samples with two classes as defined in tab. 1. Figure 3 demonstrates some sample images.

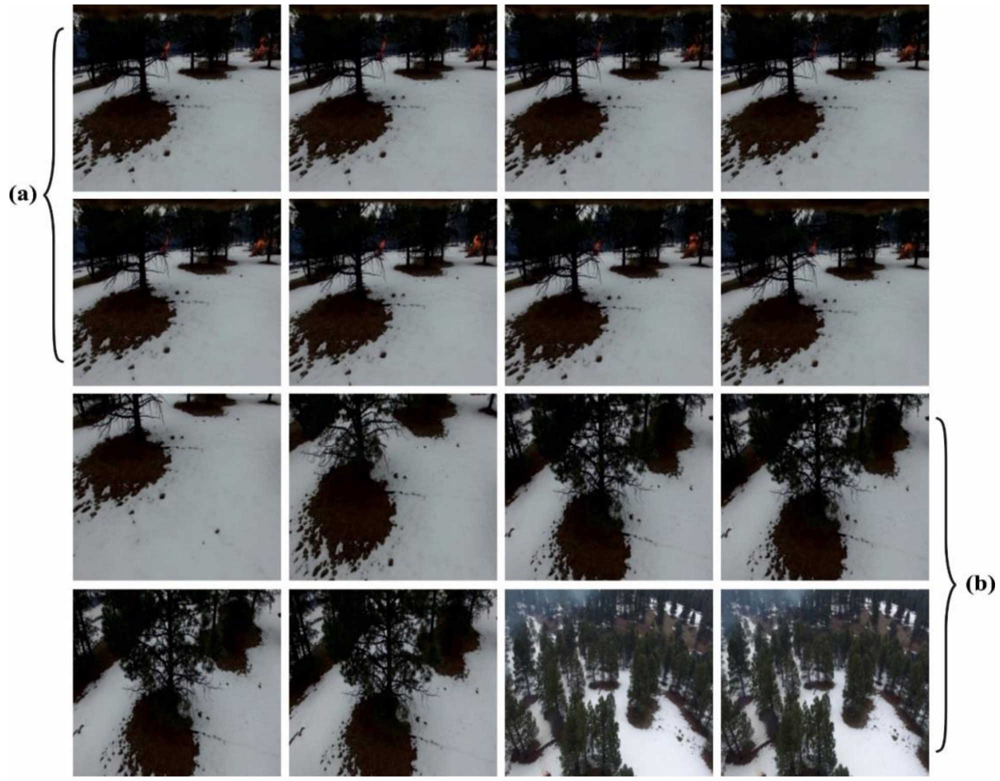

Figure 3. (a) Fire and (b) no fire

The confusion matrices provided by the DIFFDC-MDL approach are portrayed in fig. 4. The results referred that the DIFFDC-MDL model has properly detected the wild fire under all runs. For instance, on run-1, the DIFFDC-MDL model has recognized 2963 samples into fire and 2967 samples into no-fire. In addition, on run-4, the DIFFDC-MDL system has detection 2981 samples into fire and 2982 samples into no-fire. Along with that, on run-6, the DIFFDC-MDL algorithm has recognized 2979 samples into fire and 2967 samples into no-fire. At last, on run-9, the DIFFDC-MDL system has recognized 2978 samples into fire and 2972 samples into no-fire.

Table 2 exhibits the overall fire detection results of the DIFFDC-MDL model under different runs. The experimental values stated that the DIFFDC-MDL model has gained effective classification results under each run. Figure 5 reports an average $accu_y$ examination of the DIFFDC-MDL approach under several runs. The figure revealed that the DIFFDC-MDL system has obtained superior $accu_y$ values under distinct runs. For sample, on run-1, the DIFFDC-MDL technique has offered average $accu_y$ of 98.83%. Similarly, on run-2, the DIFFDC-MDL algorithm has provided average $accu_y$ of 99.03%. Likewise, on run-4, the DIFFDC-MDL technique has given average $accu_y$ of 98.22%. Finally, on run-9, the DIFFDC-MDL methodology has obtained average $accu_y$ of 98.85%.

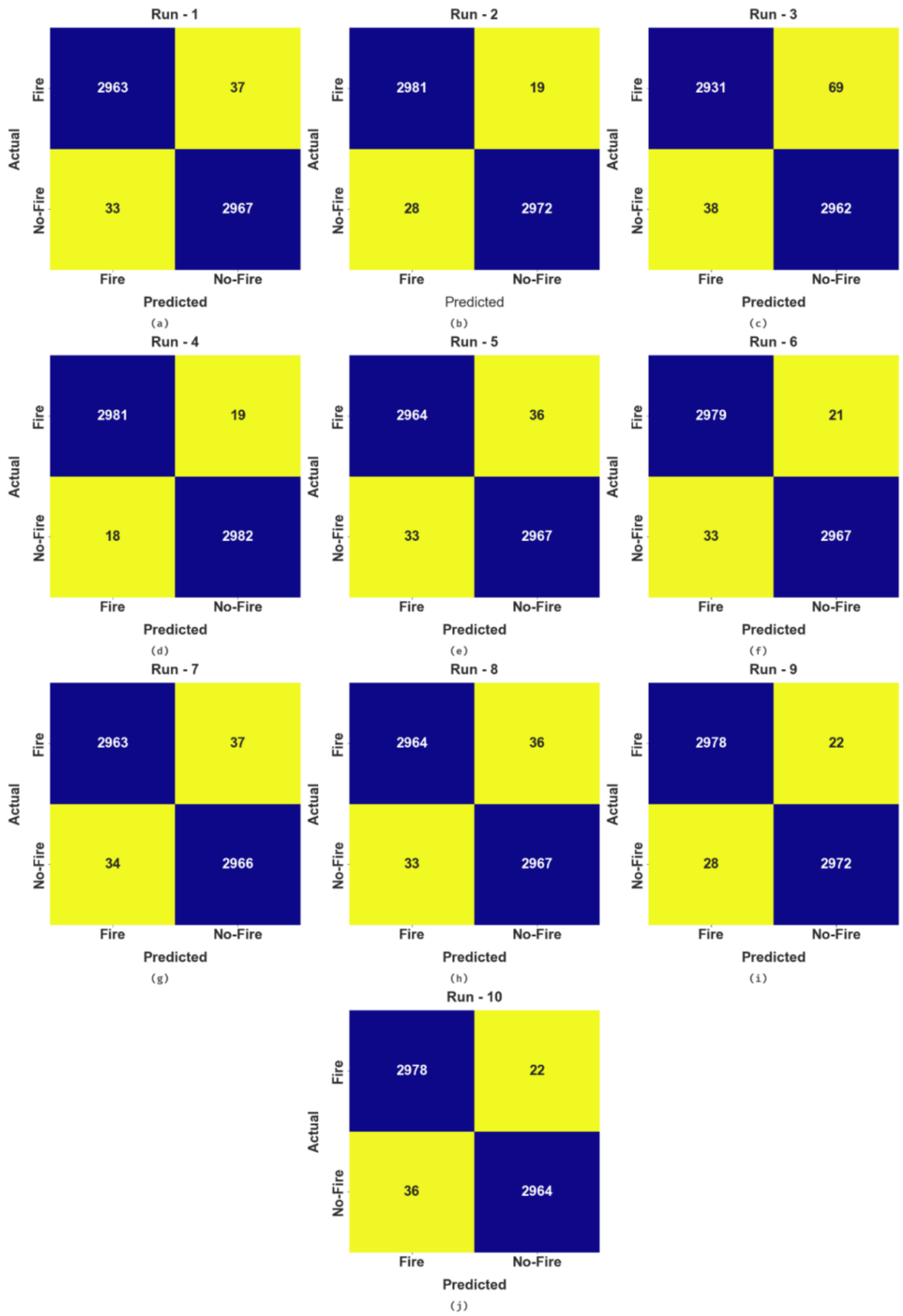

Figure 4. Confusion matrices of DIFFDC-MDL system (a-j) runs 1-10

Figure 6 defines an average $sens_y$ analysis of the DIFFDC-MDL method under several runs. The figure implied that the DIFFDC-MDL system has gained increased $sens_y$ values under distinct runs. For instance, on run-1, the DIFFDC-MDL method has reached average $sens_y$ of 98.83%. Similarly, on run-2, the DIFFDC-MDL algorithm has attained average $sens_y$

of 99.03%. Likewise, on run-4, the DIFFDC-MDL methodology has provided average $sens_y$ of 98.22%. At last, on run-9, the DIFFDC-MDL methodology has given average $sens_y$ of 98.85%.

Table 2. Result analysis of DIFFDC-MDL system with distinct runs and measures

Class	Accuracy	Sensitivity	Specificity	F_{score}	AUC Score
Run - 1					
Fire	98.77	98.77	98.90	98.83	98.83
No-Fire	98.90	98.90	98.77	98.83	98.83
Average	98.83	98.83	98.83	98.83	98.83
Run - 2					
Fire	99.27	99.27	98.80	99.04	99.03
No-Fire	98.80	98.80	99.27	99.03	99.03
Average	99.03	99.03	99.03	99.03	99.03
Run - 3					
Fire	99.37	99.37	99.07	99.22	99.22
No-Fire	99.07	99.07	99.37	99.22	99.22
Average	99.22	99.22	99.22	99.22	99.22
Run - 4					
Fire	97.70	97.70	98.73	98.21	98.22
No-Fire	98.73	98.73	97.70	98.23	98.22
Average	98.22	98.22	98.22	98.22	98.22
Run - 5					
Fire	99.37	99.37	99.40	99.38	99.38
No-Fire	99.40	99.40	99.37	99.38	99.38
Average	99.38	99.38	99.38	99.38	99.38
Run - 6					
Fire	98.80	98.80	98.90	98.85	98.85
No-Fire	98.90	98.90	98.80	98.85	98.85
Average	98.85	98.85	98.85	98.85	98.85
Run - 7					
Fire	99.30	99.30	98.90	99.10	99.10
No-Fire	98.90	98.90	99.30	99.10	99.10
Average	99.10	99.10	99.10	99.10	99.10
Run - 8					
Fire	98.77	98.77	98.87	98.82	98.82
No-Fire	98.87	98.87	98.77	98.82	98.82
Average	98.82	98.82	98.82	98.82	98.82
Run - 9					
Fire	98.80	98.80	98.90	98.85	98.85
No-Fire	98.90	98.90	98.80	98.85	98.85
Average	98.85	98.85	98.85	98.85	98.85
Run - 10					
Fire	99.27	99.27	99.07	99.17	99.17
No-Fire	99.07	99.07	99.27	99.17	99.17
Average	99.17	99.17	99.17	99.17	99.17

Figure 7 illustrates an average $spec_y$ examination of the DIFFDC-MDL model under several runs. The figure implied that the DIFFDC-MDL system has obtained higher $spec_y$ values under distinct runs. For sample, on run-1, the DIFFDC-MDL technique has offered average $spec_y$ of 98.83%. Similarly, on run-2, the DIFFDC-MDL algorithm has offered average $spec_y$ of 99.03%. Likewise, on run-4, the DIFFDC-MDL system has offered average $spec_y$ of 98.22%. Lastly, on run-9, the DIFFDC-MDL approach has offered average $spec_y$ of 98.85%.

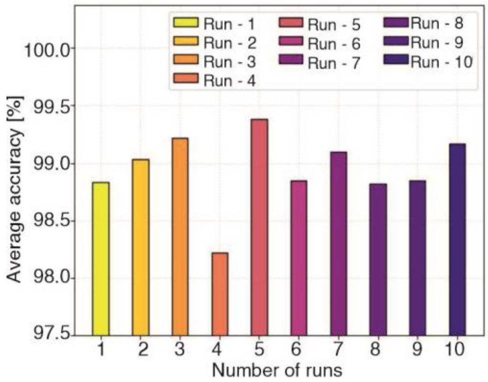

Figure 5. Average *accu*$_y$ analysis of DIFFDC-MDL system with distinct runs

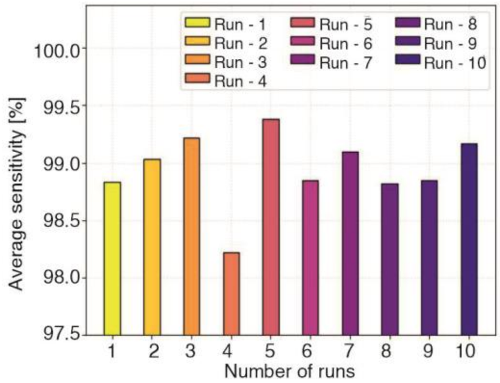

Figure 6. Average sens$_y$ analysis of DIFFDC-MDL system with distinct runs

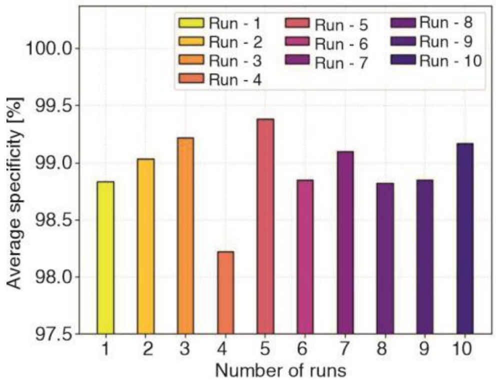

Figure 7. Average *spec*$_y$ analysis of DIFFDC-MDL system with distinct runs

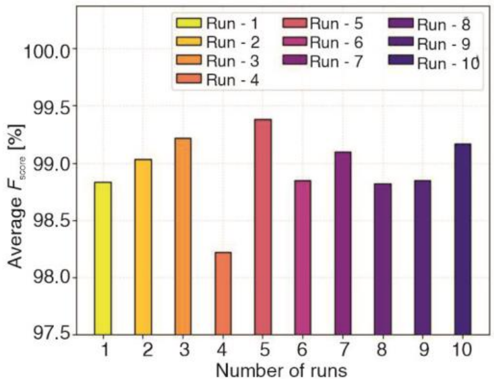

Figure 8. Average F_{score} analysis of DIFFDC-MDL system with distinct runs

Figure 8 showcases an average F_{score} examination of the DIFFDC-MDL model under several runs. The figure implied that the DIFFDC-MDL system has reached raised F_{score} values under distinct runs. For sample, on run-1, the DIFFDC-MDL approach has offered average F_{score} of 98.83%. Similarly, on run-2, the DIFFDC-MDL model has offered average F_{score} of 99.03%. Also, on run-4, the DIFFDC-MDL model has offered average F_{score} of 98.22%. Eventually, on run-9, the DIFFDC-MDL model offered average F_{score} of 98.85%.

Figure 9 demonstrates an average AUC_{score} examination of the DIFFDC-MDL model under several runs. The figure outperformed that the DIFFDC-MDL algorithm has attained maximal AUC_{score} values under distinct runs. For instance, on run-1, the DIFFDC-MDL approach has offered average AUC_{score} of 98.83%. Besides, on run-2, the DIFFDC-MDL method has offered average AUC_{score} of 99.03%. Likewise, on run-4, the DIFFDC-MDL algorithm has provided average AUC_{score} of 98.22%. Finally, on run-9, the DIFFDC-MDL approach has offered average AUC_{score} of 98.85%.

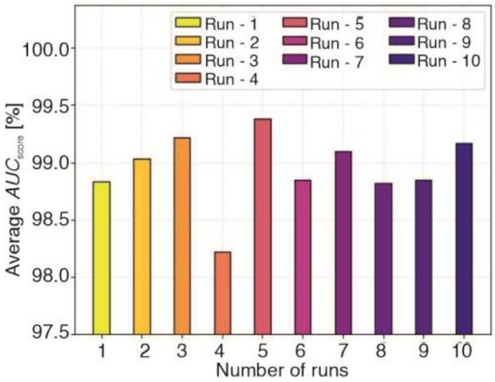

Figure 9. Average AUC_{score} analysis of DIFFDC-MDL system with disitnct runs

The training accuracy TR_{acc} and validation accuracy VL_{acc} gained by the DIFFDC-MDL approach under test database is exposed in fig. 10. The simulation result pointed out the DIFFDC-MDL system has gained increased values of TR_{acc} and VL_{acc}. In certain the VL_{acc} looked that better than TR_{acc}.

The training loss TR_{loss} and validation loss VL_{loss} realized by the DIFFDC-MDL system in the test database are exhibited in fig. 11. The simulation result represented that the DIFFDC-MDL approach has obtained lower values of TR_{loss} and VL_{loss}. Especially, the VL_{loss} is lesser than TR_{loss}.

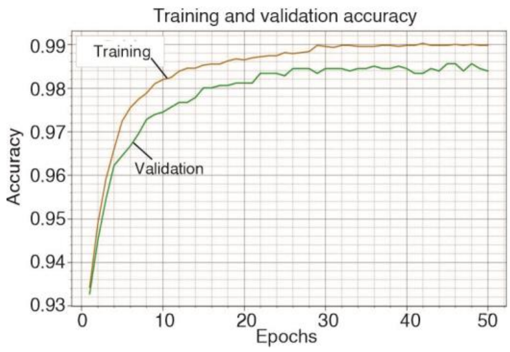

Figure 10. The TR_{acc} and VL_{acc} analysis of DIFFDC-MDL system

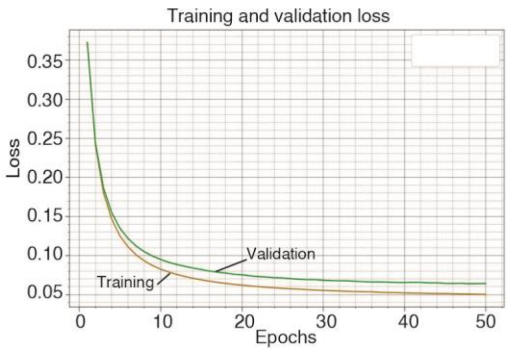

Figure 11. The TR_{loss} and VL_{loss} analysis of DIFFDC-MDL system

An observable precision-recall (PR) inspection of the DIFFDC-MDL system under test database is shown in fig. 12. The figure displaying the DIFFDC-MDL methodology has resulted to increased values of PR values in all class labels.

Table 3 and fig. 13 exhibits an overall comparison stud of the DIFFDC-MDL model. The experimental values referred that the ResNet50 method has obtained lower classification outcomes. Next to that, the VGG16 and Inception techniques have exhibited slightly enhanced classification performance. Though the KELM and LSTM models have reached competitive outcomes, the DIFFDC-MDL model has resulted to superior performance with $accu_y$ of 99.38%. These results confirmed the accurate fire detection efficiency of the DIFFDC-MDL model.

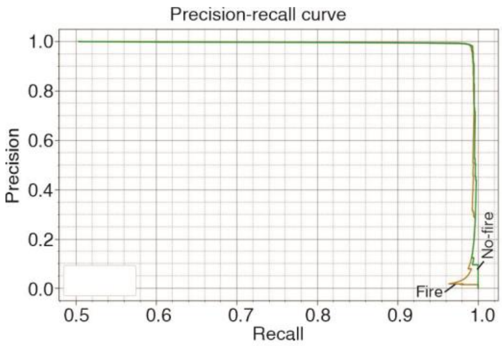

Figure 12. Precision recall analysis of DIFFDC-MDL system

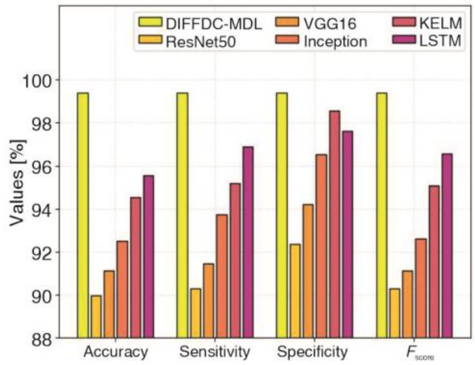

Figure 13. Comparative analysis of DIFFDC-MDL system with existing approaches

Table 3. Comparative analysis of DIFFDC-MDL system with existing approaches

Methods	Accuracy	Sensitivity	Specificity	F_{score}
DIFFDC-MDL	99.38	99.38	99.38	99.38
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

Conclusion

In this article, a novel DIFFDC-MDL system can be introduced for forest fire classification in drone images. To accomplish this, the presented DIFFDC-MDL model designs a modified MobileNet-v2 model to generate feature vectors. For forest fire classification, the SRU model is applied in this study. In order to further improve the classification outcomes, the SFLA is used for hyperparameter tuning. The simulation outcome analysis of the DIFFDC-MDL approach is tested utilizing a dataset comprising fire and non-fire samples. The extensive comparison study referred that the enhancements of the DIFFDC-MDL approach over other recent approaches. Thus, the projected DIFFDC-MDL system was utilized for FFD in real time. In future, hybrid DL systems can be employed for increasing the detection rate of the presented DIFFDC-MDL model.

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