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Research Article

Federated Learning for Smart and Sustainable Forest Fire Detection in Green Internet of Things

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ABSTRACT

With the exponential rise in the adoption of the Internet of Things (IoT), sensors have become an essential part of smart systems, enabling real-time monitoring and control in applications such as energy management, security, and safety. Among these, early fire detection is a critical application to prevent devastating consequences. This paper introduces a novel Federated Learning (FL) framework designed for the rapid detection of forest fires within smart and sustainable environments using the Green Internet of Things (GIoT). The proposed framework integrates distributed learning across multiple edge devices to detect fire incidents without compromising data privacy. It leverages a modified DenseNet121 architecture enhanced with a soft attention mechanism, capable of accurately classifying fire and no-fire scenarios even under challenging weather conditions. The dataset was augmented to simulate fog and haze, ensuring model robustness in real-world environments. The experimental results demonstrate that the proposed system achieves outstanding performance with a training accuracy of 97.8% and a validation accuracy of 97.06%, confirming its effectiveness and scalability in edge-enabled fire detection systems.

1. INTRODUCTION

As part of the regeneration process of healthy forests, forest fires (FF) play a vital role. There is, however, a significant physical and economic cost associated with FF when they occur near human communities. Therefore, it is imperative to predict the conditions that can trigger a FF ignition so that appropriate fire management resources can be allocated and communities can be protected. Energy resources have gained popularity in recent decades due to their sustainable use. According to the Global Environment and Development Commission Report, sustainability is the term most commonly used to describe development [1]. Sustainability forest operations (SFO) refers to a comprehensive approach to solving current and future problems that integrates forest activities with economic, social sustainability and environmental [2]. Forests are defined by FAO (Foundation, 2020) as land areas greater than 0.5 ha in area and more than 10% canopy cover, which are not primarily used for agriculture or other non-forest purposes. Biodiversity on earth is centered in forests. Carbon emissions are mitigated by forests, which provide livelihoods and are integral to sustainable food production. As of 2020, forests will cover 4.06 billion hectares, or 31% of the total lands, or 0.52 hectares per person, even though forests aren't allocated geographically. Tropical regions host approximately 45% of the world's forests, followed by boreal regions with 27%, temperate zones with 16%, and subtropical areas with 11%. Excluding Europe, the remaining global forest area about 25% is distributed across South America, North and Central America, Africa, Asia, and Oceania. Due to the effects of climate change, forest fires are becoming more frequent, larger, and more severe. A comprehensive study of all potential solutions to this problem is necessary, given its magnitude. We present two frameworks as contributions to ongoing research. To train ML models with FF ignition datasets, the first step is to create these datasets. Secondly, we apply Federated Learning (FL), an advanced ML approach, in combination with Internet of Things (IoT) technologies to forecast the likelihood of forest and field (FF) fire ignition or non-ignition in defined geographic regions and timeframes.

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2. RELATED WORK

Governments have used two primary methods of detecting wildfires: (1) satellite imagery and[3] drones. A satellite-based early detection system was proposed by the authors of [5]. Data from satellite maps was input into a detection algorithm using thermal and infrared readings. An image-based satellite system for Russia was also proposed by authors in [4]. Wildfires can be difficult to control due to their size and remoteness, but the system attempts to resolve that problem. A global satellite imagery system was deployed by NASA to monitor rain forests in the southwest Amazonian rain forest. Hotspots (fires) are reported in real time using multisensory technology [5]. In [6],[7] satellite imagery and machine learning algorithms are used to detect wildfires over vast areas early, increasing firefighting response time. Multi-modal satellite data integration can greatly improve fire detection systems' accuracy, according to studies like [8] and[9] As well as providing broad coverage, these technologies also allow automatic fire perimeter mapping, which is important to deploying resources effectively and suppressing fires effectively. Due to their scalability and capacity to cover vast areas, satellites are crucial for effective wildfire management and reducing environmental damage. As a result, satellite-based technologies have become integral to contemporary fire management approaches, enhancing both the precision and efficiency of firefighting operations.

Research has investigated the use of AI in wildfire science and management in a number of surveys and studies. As part of these studies, researchers explored the potential for supporting prevention, detection, response, and restoration aspects of fire management. This review discussed fire behavior modeling, decision support systems and fire spread prediction for fire management [10]. According to a study, AI can improve fire management practices by improving the accuracy and reliability of fire predictions. Fire detection using remote sensing data was the focus of an interesting survey conducted by the author [7] . Fire detection accuracy can be improved significantly through SVM, ANN, and DT, according to the study. A recent study by [4] focused on the application of algorithms in wildfire preparedness. A comprehensive review of various algorithms is presented in this study, which highlights how they can improve wildfire preparedness and response. Wildfire science and management are experiencing a growing interest in these methods, which can help to improve fire management practices. The performance of FL is currently being studied in various ways. In FL, nodes crash and move, and latency increases as nodes are added. Additionally, clients and servers transmit more data than ever before. A summary of existing research is presented in Table I.

TABLE I: RESEARCH ANALYSIS BASED ON THE EXISTING SYSTEMS

Author	Methods	Advantages	Research Challenges
[11]	Federated matched averaging (FedMA) algorithm	In FedMA, hidden elements are used to extract signatures for constructing a shared global model	Inadequate privacy protections, data bias
[12]	Federated Optimization	The mobile device is built as a computing node	Neither a dataset nor a theoretical basis exists
[13]	FL and Red Fox Optimization	Operation of workers and servers is combined	There is a random selection of parameters and a longer execution time
[14]	Aqua-Fel PSO	It is possible to detect water pollution and estimate its quality	The estimation of multiple water quality parameters is not performed
[15]	PSO + FL = PAASO	Agents can optimize functions by understanding their function	In heterogeneous environments, it does not perform well
[16]	PSO and FL	During client aggregation, PSO optimizes eight clients	It is possible to improve FL models further since they are not stable
[17]	FPSO-FS algorithm	Multi-participant involvement in PSO can lead to optimal private subsets, while FL can address privacy issues	It takes a long time to execute

3. THE PROPOSED FRAMEWORK

In this framework, three main steps are involved: preprocessing and augmentation of data, training, and testing. In the data pre-processing phase, we augmented the dataset with uncertainty using data augmentation techniques. A modified version of DenseNet121 with a soft attention module was used to detect fires in both normal as well as adverse weather conditions. In the subsequent sections, we describe the major components of the framework.

3.1 Data Pre-Processing and Data Augmentation

By analyzing images with DL, we can classify, segment, and detect objects in scenes more effectively. This unexpected situation is most commonly caused by domain shifting problems. This unexpected situation is most commonly caused by domain shifting problems The actual weather can differ from the training data during the deployment phase due to fog or haze. Training data captured in normal weather conditions is used to train DL models. For the detection of fires, DL models are augmented with data.

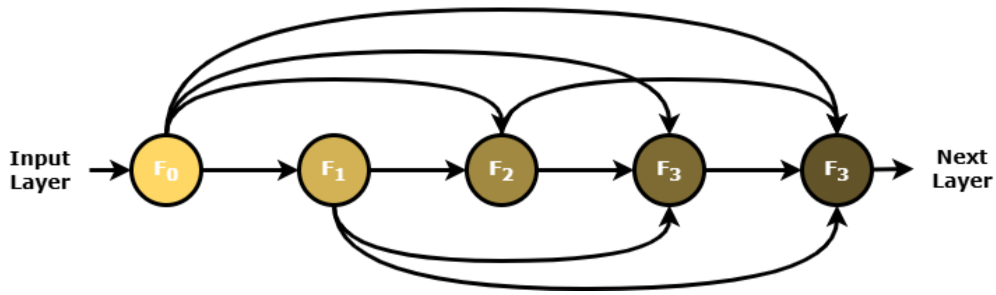

Fig. 1. The block diagram of the DenseNet.

$$I(x)t(x) + A\big(1 - t(x)\big) \tag{1}$$

$$t(x) = e^{-\beta d(x)} \tag{2}$$

I(x) denote the observed hazy image, $J(x)$ refers to the origin input image. The parameter A signifies the global atmospheric light, and $t(x)$ stands for the medium transmission map. Based on the transmission $t(x)$ a new image I(x) can be formulated using Eqn. (1). When atmospheric light is assumed to be uniform, the transmission $t(x)$ can be modeled by using Eqn. (2), where β is the atmospheric scattering coefficient and $d(x)$ represents the depth map of the scene.

It is necessary to randomly select β values between 1.0 and 3.0 in order to avoid generating similar haze across all images. Choosing β in this manner results in more diverse training datasets, as the amount of haze can be varied. Additionally, a synthetic fog algorithm augments the dataset to make the model more robust in a foggy environment. Adding the fog requires only a small change in A and $t(x)$ while keeping the same equations (1) and (2) [18] ,[19] ,[20]. A normalised depth matrix of 0 to 1 can be determined by mono-depth [18]. When A=1, white fog is applied to the image, whereas A=0 results in the introduction of black fog. As the transmission map $t(x)$ varies between 0 and 1, it reflects the proportion of the original image and the fog retained in the resulting image. As illustrated in Eqns. (3) and (4), the objective function integrates two types of loss: an adversarial loss and a cycle consistency loss.

$$L_{GAN}\big(G, D_{Yf}, X_f, Y_{f,}\big) = E_{yf\ Pdata(yf)}\big[log D_{yf}(yf)\big] + E_{xfPdata(xf)}\big[log 1 - D_{yf}(G(xf))\big]. \tag{3}$$

$$L_{cyc}(G, F) = E_{xfPdata(xf)}\big[\big\|F\big(G(xf)\big)\big)\ xf\big\|1\big] + E_{yf\ Pdata(yf)}[\|G(F(yf))\ yf\|]1. \tag{4}$$

It is therefore possible to write the objective function as follows:

$$L\big(G, F, D_{xf}, D_{yf},\big) = L_{GAN}\big(G, D_{yf}, X_f, Y_{f},\big) + L_{cyc}(G, F). \tag{5}$$

Synthetic night-time images were created from preprocessed side-rectilinear images using the trained generator to expand the number of samples.

3.2 Feature Extraction

Using multi-scale features extraction, we extract backbone features. Multi-scale features are merged using densely connected structures to achieve more effective semantic relationship detection compared to traditional CNNs. CNNs can be highly effective at classifying fire scenes. As a result, Dense Net was employed in order to create deeper, densely connected networks in order to solve those problems. Dense Net's densest blocks improve layers' information flow [10]. A proposed model transmits feature maps from all layers by receiving inputs from all preceding layers. Feature transmission is enhanced by short connections between input and output layers. The architecture allows us to extract the most significant and global features necessary to train models efficiently and effectively. Feature maps are integrated using all previously collated layers as input, as shown in Figure 1.

It is required to have $L\left(\frac{L+1}{2}\right)$ connections in conventional network architectures. By using the previous layers, such as $F_{o,} \dots, F_{t=1}$, as shown in Eqn. 6, the input features can be computed, namely a map of I.

$$(\ F_l = T_l([F_0, F_1, \dots, F_l - 1]) \tag{6}$$

Here, $0,1,2, \dots, l - t$ denotes the layer from which the feature maps have been concatenated. As opposed to using a pointwise sum, the feature maps are concatenated instead. Among the nonlinear transformations $T_l(.)$ in Eqn. (6) are convolutions, poolings, and activations. Various assets are incorporated into each dense block of our proposed model, along with convolutional layers that make use of similar padding mechanisms when combining them. The dense connectivity of this structure reduces the number of parameters required compared to traditional CNNs. A network layer requires less feature maps since redundant information is eliminated due to the network architecture. As each layer is concatenated continuously, it has access to the gradients from the first input data as well as loss function, greatly improving learning efficiency. By allowing information to be accessed rapidly between layers, gradient disappearance can be reduced as well as the information flow can be improved.

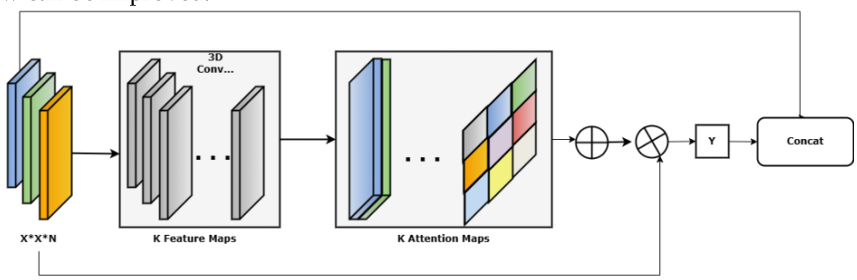

Fig 2. The soft attention mechanism of proposed model.

In spite of Dense Net's strong capability to extract features in the spatial domain, most fires are caused by adverse weather conditions, which reduce visibility and clarity. The K feature attention model presented in Figure 2 shows how the model is based on K features.

3.3 Model Training Improvement with Hyperparameters Selection

Federated Averaging (FedAvg) optimizes the training of a global model although preserving data decentralization simultaneously. The procedure requires multiple communication loops. Each new round of participation selects a subset of customers. The current global parameters model θ_i, measure the local gradient $\nabla L_i\ (\theta_G)$ according to the local loss function $L_i(\theta)$, and its update its local parameters using a local optimize by Eqn. (7) and (8). The learning rate is chosen to be 0.001 in the proposed federated learning model.

$$\theta_{i\ (new)} = LocalOptimizer\big(\theta_G, \nabla L_i(\theta_G)\big) \tag{7}$$

$$\theta_{i\ (new)} = \theta_G - \mu \nabla L_i(\theta_i) \tag{8}$$

Federated learning requires aggregation of these deviations on the central server (CS) to obtain the updated (θ_G).
In federated learning, changes are aggregated on a central server and an updated (θ_G) is formed. Clients update their local datasets during the local training phase. The aggregation procedure in federated learning facilitates collaborative learning while protecting individual clients' privacy. The central server updates the model parameters after each client completes their local training. A model change may be sent to the server by multiple clients, but not every client will participate in every communication cycle. It is possible to select customers randomly by using N, which indicates how many will be chosen. The server computes new global model parametersθ_G (new) by averaging the model updates provided by the chosen clients. A weighted average ensures that the contribution of each client is proportionate to their number of updates. $\theta_{G\ (new)}$ Client i provided updated parameters for the model. This summation shows the current round's iteration over all selected clients. Division by N ensures that all selected clients have equal influence on the average model. There are i samples of data at client i, so m_i is the number of samples. Thus, the global model represents all the customer insights and information precisely. Due to the diversity and non-IID (non-independent and identically distributed) nature of client datasets, weighted averaging is imperative. Due to the diversity and non-IID nature of client datasets, weighted averaging is imperative. Data imbalances between clients are reduced by federated learning, and overfitting is prevented by aggregating updates proportionally to updated data from each client.

$$\theta_{G\ (new)} = \frac{1}{N}\sum_{i=0}^{N}\big(m_i \times \theta_{i\ (new)}\ \big)$$

3.4 Validation Metrics

For fire detection, the proposed model is evaluated for generalizability and overfitting. Training, testing, and validation phases were conducted on each data set. Training and test sets are generated from 80% and 20% samples of the dataset. The proposed model is evaluated based on accuracy (Acc), reliability (DR), accuracy (FAR) and precision (F1)-scores[21]. The proposed model uses the equations developed for the $TP, TN, FP,$ and FN to calculate the used metrics [21], [22]:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

$$DR = \frac{TP}{TP + FN} \quad (12)$$

$$FAR = \frac{FP}{TN + FP} \quad (13)$$

$$F1 = 2 \times \frac{TP}{2 \times TP + FP + FN} \quad (14)$$

The average of the training and validation times is used to evaluate cross-validated models. F1-scores should be high, and execution times should be short in a good ID.

4. PERFORMANCE EVALUATION

All experiments were conducted using Python, leveraging the scikit-learn machine learning library, which provides a collection of open-source classification algorithms. The model's performance was tested on Intel Core i5 dual-core processor with 8GB of RAM Window based System. The dataset used in this study was specifically compiled to tackle the challenge of forest fire detection. It consists of color images (3 channels) with a resolution of 250 × 250 pixels. These images were sourced through various search engines using relevant keywords. After collection, each image underwent careful preprocessing to eliminate irrelevant elements such as people or fire-fighting equipment, ensuring that only the regions depicting fire or no fire were preserved. The dataset was designed for a binary classification task, distinguishing between Fire and No Fire in forest landscapes. The few sample of the dataset image is shown in Figure 3. The dataset consists of 1900 images split into five classes, each with 950 samples. A dataset with 80% for training and 20% for testing was used for model evaluation.

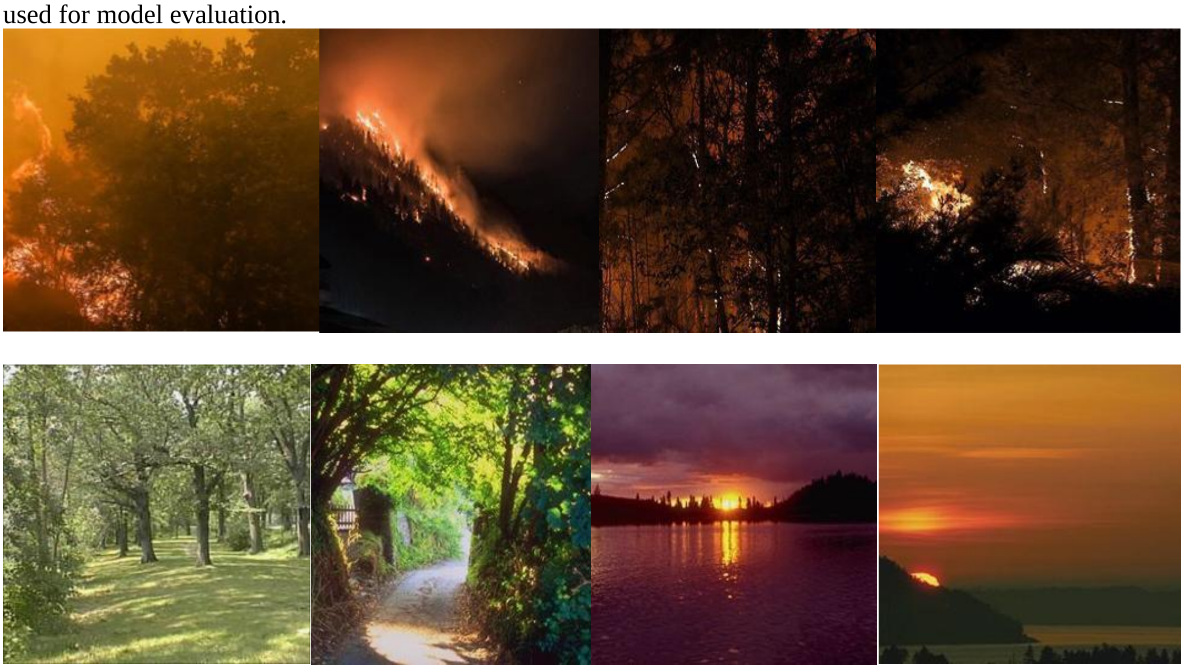

Fig. 3. Sample image of the dataset.

The training results of the proposed model demonstrate its strong performance and excellent generalization capability. Over the course of 10 epochs, the model shows a consistent increase in training accuracy, starting from 72.75% in the 1^{st} epoch and reaching 97.74% by the 10^{th} epoch as shown in Figure 4. Correspondingly, the training loss steadily decreases from 0.5498 to a minimal value of 0.0632, demonstrating that proposed model is efficiently learning the patterns in the training data. The validation accuracy also follows a positive trend, peaking at 97.06% in the final 2^{nd} epochs, with the validation loss reducing significantly to 0.0692. Although there is a minor fluctuation in validation accuracy during epochs 2^{nd} and 6^{th}, the model quickly recovers and maintains high performance thereafter. Notably, the best performance is observed in the 10^{th} epoch, where the model achieves both high accuracy and low validation loss, confirming its robustness and minimal overfitting. Overall, these results suggest that the proposed model is well-optimized, stable, and highly accurate in handling the classification task, of the forest fire detection.

```
Epoch 1/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 257s 4s/step - accuracy: 0.7275 - loss: 0.5498 - val_accuracy: 0.8382 - val_loss: 0.3873
Epoch 2/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 109s 2s/step - accuracy: 0.9391 - loss: 0.1720 - val_accuracy: 0.8088 - val_loss: 0.5296
Epoch 3/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 102s 2s/step - accuracy: 0.9529 - loss: 0.1319 - val_accuracy: 0.8824 - val_loss: 0.3021
Epoch 4/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 101s 2s/step - accuracy: 0.9605 - loss: 0.1079 - val_accuracy: 0.8824 - val_loss: 0.3442
Epoch 5/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 152s 2s/step - accuracy: 0.9436 - loss: 0.1621 - val_accuracy: 0.9265 - val_loss: 0.2191
Epoch 6/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 101s 2s/step - accuracy: 0.9691 - loss: 0.1015 - val_accuracy: 0.8088 - val_loss: 0.3052
Epoch 7/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 102s 2s/step - accuracy: 0.9768 - loss: 0.0720 - val_accuracy: 0.9118 - val_loss: 0.1711
Epoch 8/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 101s 2s/step - accuracy: 0.9781 - loss: 0.0809 - val_accuracy: 0.8529 - val_loss: 0.2266
Epoch 9/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 101s 2s/step - accuracy: 0.9750 - loss: 0.0711 - val_accuracy: 0.9706 - val_loss: 0.0743
Epoch 10/10
58/58 ━━━━━━━━━━━━━━━━━━━━ 99s 2s/step - accuracy: 0.9774 - loss: 0.0632 - val_accuracy: 0.9706 - val_loss: 0.0692
```

Fig. 4. Performance analysis of the proposed model.

To evaluate the performance of the proposed model, it was trained and tested on a fire detection dataset consisting of labeled images categorized into two classes: fire and no fire. During the training and testing phases, both accuracy and loss metrics were calculated to assess the model's learning efficiency and generalization capability. The results are visually represented in Figure 5 (a) and Figure 5 (b), which illustrate the combined training and testing accuracy and loss curves of the proposed model across all epochs. Additionally, the performance of the proposed model was compared with an approach that utilizes the entire image for classification without region-based analysis. The comparative analysis clearly indicates that the proposed model outperforms the baseline method, achieving a high training accuracy of approximately 97.8% and a testing (validation) accuracy of around 97.06%. These results confirm the robustness and effectiveness of the proposed model in accurately detecting fire-related instances from image data.

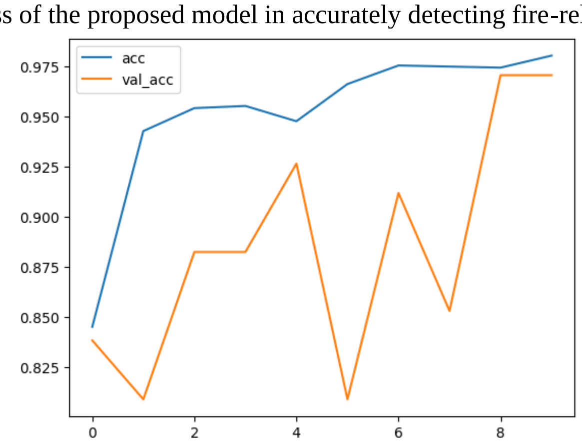

Fig. 5(a). Performance analysis of the accuracy of the proposed model versus number of epoch.

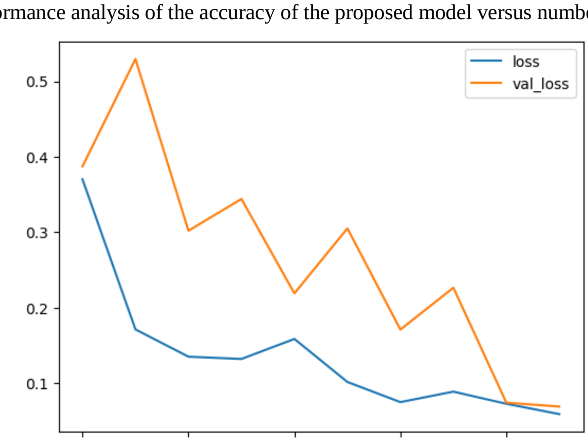

Fig. 5(b). Performance analysis of the loss of the proposed model versus number of epoch.

Figure 6 illustrates the classification of fires using images and feature maps. Feature selection and hyperparameter optimization, otherwise known as classification, form the main parts of the proposed model. Rows 1 and 2 show the results of classification. Fire and no fire classification text messages are visible in images. The proposed model was also evaluated based on accuracy using the equations above. These results demonstrate that our model is very accurate and efficient.

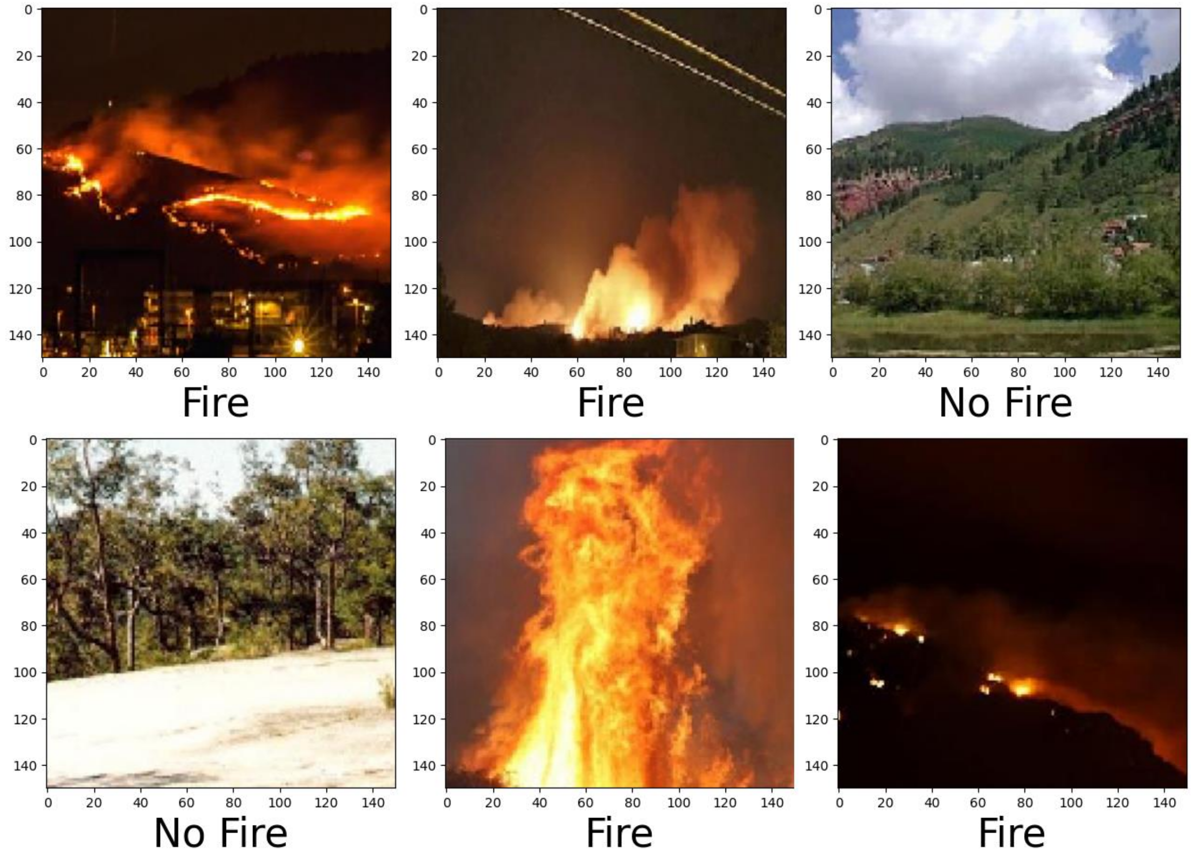

Fig. 6. Classification result of the proposed model.

5. CONCLUSION

In this study, we proposed a federated learning-based framework for intelligent and sustainable forest fire detection, leveraging the capabilities of edge computing and Green IoT. The system was designed to address key challenges such as data privacy, environmental diversity, and model robustness under adverse weather conditions. By incorporating a modified DenseNet121 with a soft attention module and performing extensive data augmentation (including synthetic fog and haze), the proposed model achieved highly accurate and generalized performance on a curated, balanced dataset. The federated learning approach allowed decentralized model training across multiple clients, effectively handling non-IID data and reducing the risk of overfitting. The experimental evaluation confirmed the effectiveness of the model, reaching 97.8% accuracy on training data and 97.06% on testing data, along with high precision and recall values. These results validate the potential of federated deep learning approaches in building reliable and scalable fire detection systems that can be deployed in real-time forest monitoring environments. Future work will explore advanced communication-efficient FL techniques and more diverse datasets for global deployment.

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Conflicts of Interest:

The authors declare that they have no conflicts of interest in relation to this work.

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