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Research Article

Fire Detection from Forest Images Using Multiple Deep Learning Models

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Abstract – Forest fires can occur from natural or unnatural causes. While unnatural fires usually consist of flammable materials thrown around unconsciously; Natural fires occur regularly depending on forest cover, forest type, soil type and climate. Within the scope of this study, fire detection processes were carried out with artificial intelligence using open source dataset in order to detect fires in forests. The dataset used includes fire and non-fire images. There are 480 images in total, 240 for each class in the binary classification study. For classification, special attention has been paid to the equal distribution of classes so that the network training in deep learning models can be carried out in the best way. The dataset is randomly split into 80% train, 20% validation. The dataset distribution consists of 384 images for training and 96 images for validation. Artificial intelligence-based deep learning models used for classification are Residual Networks (ResNet), Bidirectional Encoder representation from Image Transformers (BEiT) and Swin Transformer. When the fire detection results were examined, it was observed that the classification accuracies were above 87% and the f1-score was above 86%. In future studies, hybrid and/or ensemble models can be developed by using more deep learning models to further improve the detection process.

Keywords – Artificial Intelligence; Deep Learning; Fire Detection; Image Classification.

I. INTRODUCTION

Forest fires can occur due to both natural and unnatural and mostly human-induced reasons. Wind, meteor, high temperature and lightning strikes can be counted among the natural reasons for forest fires. When the causes of forest fires, which are largely caused by human activities other than natural reasons, are examined, it is observed that they occur in cases such as accidental ignition, deliberate fire, uncontrolled agriculture. When both types of causes are investigated in detail, it is understood that human-induced forest fires occur at a higher rate than naturally occurring forest fires. Different geographical regions, weather conditions and fire characteristics can also be effective in the occurrence of forest fires. In addition, climate, soil and forest type can also cause forests to occur [1].

In this study, fire detection operations were performed using deep learning and transformer-based models on an open source dataset containing fire and non-fire images in forests. The main differences of the study from the literature and its contributions to the literature are listed in items.

- In the open source dataset related to fire detection, a forest image dataset was used that was specific to the study and balanced in each class by focusing on forest fire images.

- The distribution of the dataset is random and fire detection results are analyzed in detail by using evaluation metrics such as f1-score, presicion, accuracy which are necessary for classification.
- In order to perform fire detection operations on forest image images, classification operations were implemented with many deep learning models associated with convolutional neural networks and transformers, without relying on a single model.
- Along with the fire detection operations performed using many deep learning models, the deep learning model that is specific to this study and has the best performance was found.

II. RELATED WORKS

A detailed review of the literature shows that there is a wide range of artificial intelligence studies related to fire detection. Abdusalomov et al. performed fire detection operations with Detectron2 using a custom forest fire images dataset collected from platforms such as Bing, Flickr, Google and Kaggle and achieved a precision value of 99.30% [2]. Yar et al. proposed a modified soft attention mechanism (MSAM) model based on the MobileNet deep learning model using ADSF, DFAN and FD datasets and found accuracy values over 90% in three different datasets used within the scope of the study for fire detection [3]. In order to perform fire detection operations in forests, two different YOLO versions were used in camera images obtained from Unmanned Aerial Vehicle by Shamta and Demir and high performance was achieved with the YOLOv8 deep learning model [4]. Titu et al achieved 95.21% accuracy in fire detection operations using 4 different deep learning based approaches, namely detection transformer (DETR), YOLOv8, knowledge distillation with Autodistill, and Detectron2 [5].

In a study developed by Jin et al. using their own dataset consisting of a large number of forest fire images, a lightweight SWVR algorithm including Simple Parameter-Free Attention Module (SimAM) and Reparameterization Vision Transformer (RepViT) deep learning models was proposed and the model detected forest fires with an accuracy value of 79.6%, providing high performance with low computational cost [6]. In a study designed by Zhao et al. using a dataset created from urban fires and real-world forest images, a new framework called FSDF (Fire Segmentation-Detection Framework) was proposed, which performs unsupervised fire detection and image segmentation with Vector Quantized Variational Autoencoders and YOLOv8 by extracting texture (Complete Local Binary Pattern) and color (Hue, Saturation, Value) features, and this method has demonstrated its success with robot-assisted field tests in real fire scenarios by providing significant improvements in accuracy, sensitivity and F1 score compared to YOLOv8 [7]. In the study published by Cheknane et al. using a dataset created from images of different areas such as open and closed obtained from recorded videos, a Faster R-CNN based two-stage deep learning architecture was proposed, which included a hybrid feature extractor that takes into account dynamic and static features, and the model achieved 96.5% accuracy in fire detection, demonstrating that smoke and flame were successfully detected in both closed and open environments [8].

El-Madafri et al. proposed a novel hierarchical domain-adaptive learning framework based on customized EfficientNet to overcome the limitations of traditional CNN in different forest environments using a dual-dataset of non-forest and forest fire scenarios; this approach reduces false positives and achieves high performance in fire detection results by using special layers for forest-specific details and general feature extraction over shared layers [9]. In a study developed by Yusunov et al. using a special dataset consisting of a large number of images, a transfer learning based forest fire detection approach that can detect small fires remotely day and night, supported by data augmentation techniques and combining the TranSDet structure with the pre-trained YOLOv8 model was proposed; the model showed high success for early and accurate detection of fires [10]. In a study developed by Sharma et al. using a multimodal dataset consisting of thermal camera images and fire sensor data, a multimodal fire detection approach using BiLSTM-Dense for sensor data and DenseNet models for image data was proposed; the model detected fire leaks with high accuracy while preserving privacy with its federated learning-based structure and demonstrated strong performance [11].

Yang et al. presented a model based on a fifth version YOLO with Squeeze-and-Excitation module integrated for classification and image filtering, which is suitable for embedded and lightweight systems, using a dataset generated from a large number of internet images and associated with fire; the proposed model performed very well in real-time fire detection for smart city fire monitoring systems with high accuracy and fast processing time [12]. Yu and Kim developed a deep learning-based fire detection algorithm to reduce false alarms caused by smoke detectors by using thermal camera and heat detector data with images trained with a seventh version YOLO deep learning model, and the proposed model was able to provide a very important solution in early fire detection by detecting only real fires caused by heat, achieving 92.22% accuracy [13]. In a study conducted by Yar et al. a new ViT deep learning model with both local self-attention and shifted patch tokenization was proposed using a study-specific fire dataset, and 93.5% accuracy was achieved in real-time fire classification with reduced computational cost and the ability to learn from scratch on small to medium size datasets [14].

Buriboev et al. suggested a fire detection model combining deep CNN with contour analysis and color features using a labeled dataset containing complex scenarios and small fire samples, and found an accuracy of 99.4% [15]. Using a study-specific dataset collected from fire and non-fire images, Xu et al. improved the Efficient Layer Aggregation Network structure in the seventh version YOLO with Convolutional Block Attention Module and ConvNeXtV2 to provide a new deep learning-based model that can perform fire detection with very high success [16].

Considering the artificial intelligence-based models in the literature related to fire detection, it is observed that various versions of the deep learning-based YOLO model, Transformer-based models and many other deep learning-based models are used to solve classification, object detection and segmentation problems. Within the scope of this study, fire detection operations in a two-class structure were performed with different deep learning based models from open source forest images.

III. MATERIALS AND METHOD

In the study, a fire dataset shared as an open source from the Kaggle platform was preferred to perform fire detection operations on forest images [17]. Although there are many different types of fire in this dataset, operations were performed only on images related to forest within the scope of this study. There are basically two different classes in the dataset used, fire and non-fire. This dataset consisting of forest images contains 480 images in total, 240 in each class. The dataset was randomly divided into two as 80% and 20%, respectively, for training and validation operations. As a result of this process, a total of 384 images were used as fire and non-fire images, 192 in each, in the training of the deep learning models used in the study. In the validation phase, a total of 96 remaining fire and non-fire images were preferred, 48 for each class. Details regarding the distribution of the forest images dataset are given in Figure-1. In addition, sample images for each class in the dataset are given in Figure-2.

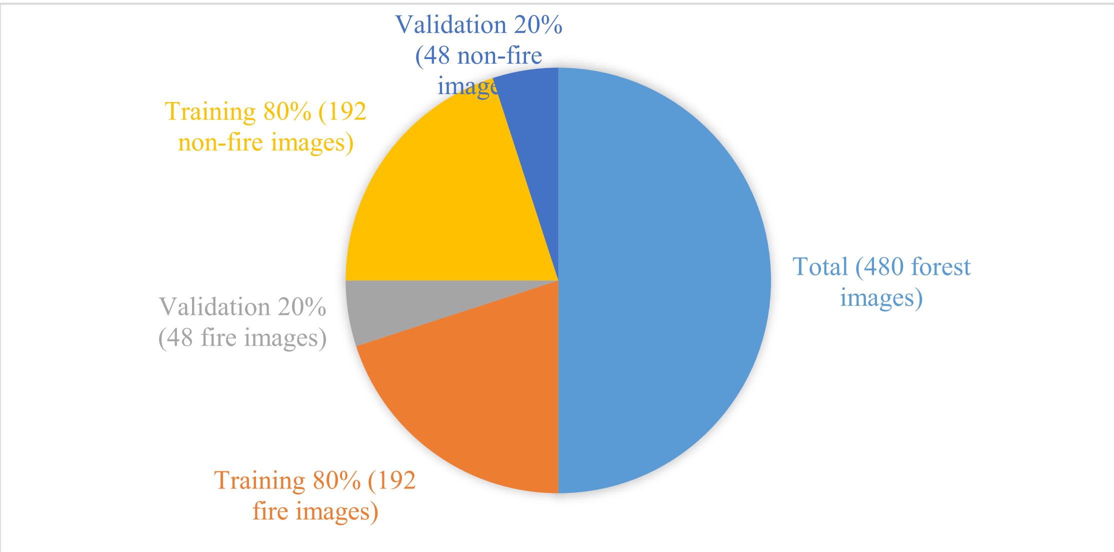

Fig. 1 Detailed dataset distribution percentage and amounts

a) Non-fire images

b) Fire images

Fig. 2 Samples related to fire and non-fire images [17]

In the image dataset consisting of fire and non-fire images, sample samples of which are shared in Figure-2, after the dataset distribution is performed as specified in Figure-1, three different deep learning based models, namely Residual Networks (ResNet) [18], Bidirectional Encoder representation from Image Transformers (BEiT) [19] and Swin Transformer [20], were used for fire detection operations. The versions of these deep learning models, one of which consists of residual blocks and the other two are transformer based, were preferred for use in all of them [21]. The flowchart for this study related to fire detection is given in detail in Figure-3 below.

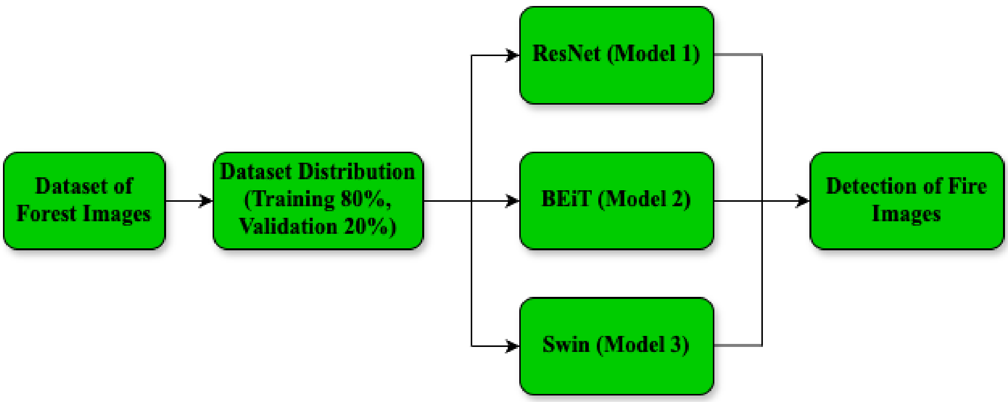

Fig. 3 Detailed fire detection flowchart

IV. RESULTS

As a result of the fire detection process, accuracy, precision, recall, f1-score and AUC (area under the receiver operating characteristic curve) values, which are frequently used and important evaluation metrics in classification problems, were obtained for each model. The graph of the metric results obtained with ResNet, BEiT and Swin transformers models used in the study is given in Figure-4 shown in below.

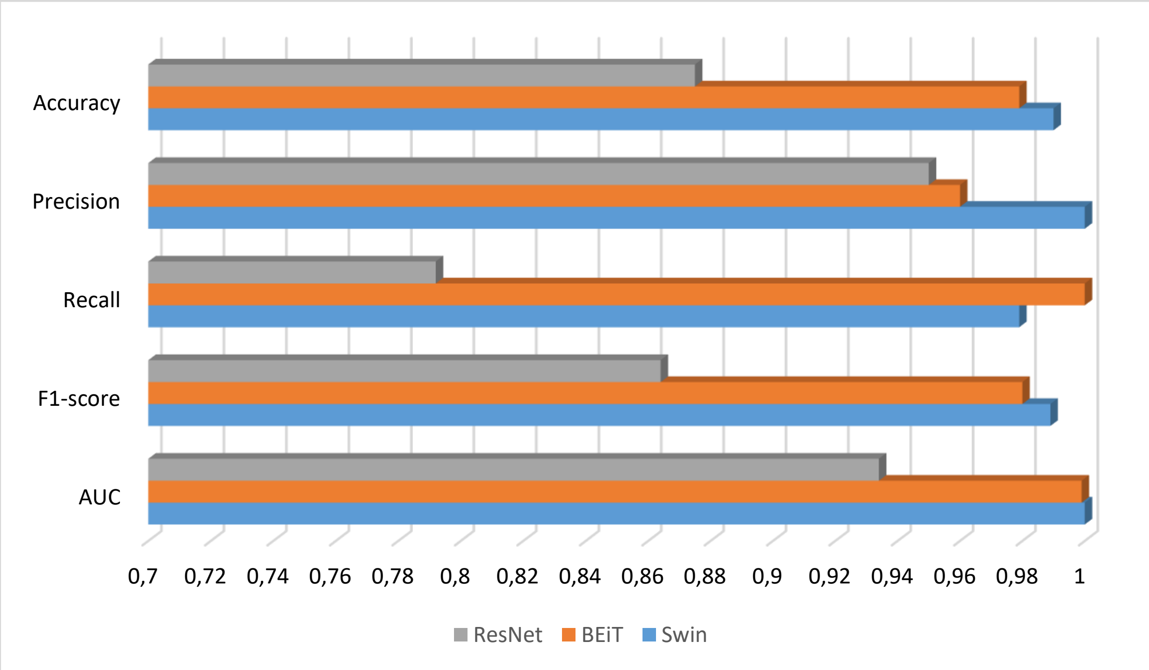

Fig. 4 Results of fire detection evaluation metrics

Figure-4 above shows that the ResNet model obtains the lowest value for all five different metrics. Moreover, when analyzed in detail, the ranking of the classification results for the other four metrics, except recall value, is ResNet, BEiT and Swin transformers from low to high. While the model with the highest recall value is BEiT, the highest classification results in precision, recall, f1-score and AUC values are obtained in the Swin transformers model. The numerical values of the fire detection results obtained with the deep learning (DL) models used in the study are given in Table-1 in detail.

Table 1. Comparison of fire detection results

DL Models	Accuracy	Precision	Recall	F1-score	AUC
ResNet	0.875	0.950	0.792	0.864	0.934
BEiT	0.979	0.960	1.000	0.980	0.999
Swin	0.990	1.000	0.979	0.989	1.000

According to the fire detection results detailed in Table-1, the highest accuracy value is 0.99 and the highest f1-score value is 0.989 for the Swin transformers model. When analyzed in terms of complete results, it is observed that Swin transformers is the best in precision, BEiT in recall and Swin transformers in AUC. In terms of all metric results as a whole, the performance ranking for classification in these three deep learning models is ResNet, BEiT and Swin transformers, respectively.

V. CONCLUSIONS

Using an open-source fire dataset that includes forest images and fire images and non-fire images, this study uses multiple deep learning models to perform various binary classification processes to detect fires. For these operations, three different deep learning models based on convolutional neural networks, two based on transformer and one based on residual block, were used. In the results achieved with the fire detection processes, it was observed that the transformer-based models gave better results. In this study, where five basic evaluation metrics were acquired for the analysis of the results, it was selected to perform classification processes for fire detection. In future studies, in addition to classes, classification and object detection or classification and segmentation can be performed together, especially by determining and labeling the boundaries of the objects in the datasets. In this way, real-time studies can be performed and fire detection applications that facilitate daily life can emerge. For this, machine learning and deep learning models, which are frequently used in the literature, can be used in ensemble or hybrid structure to contribute to fire detection.

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