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An Efficient Model for Forest Fire Detection using Deep Convolutional Neural Networks

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Abstract—Forest fires are a significant natural disaster that causes extensive damage to both human and wildlife habitats. Early detection and management of forest fires are critical in preventing potential losses. In recent years, deep learning-based approaches have emerged as promising solutions for forest fire detection. This paper proposes a deep learning-based approach for forest fire detection using SqueezeNet model.The proposed approach utilizes still images captured from forest areas under different weather conditions to classify whether an image contains a fire or not. The models were trained and tested using accuracy, precision, and recall metrics. The experimental results show that SqueezeNet achieve high precision, and recall in detecting forest fires.SqueezeNet is a Convolutional Neural Networks (CNN) architecture designed to reduce the number of parameters and computations required in a deep learning model while maintaining high accuracy in image classification tasks..

Keywords-Deep Learning; Image Processing; Convolutional Neural Networks (CNN); EfficientNet; SqueezeNet.

I. INTRODUCTION

Forest fires are a major environmental hazard that can cause significant damage to natural resources, wildlife, and human lives. Early detection and immediate response are critical to prevent and mitigate the impact of forest fires. In recent years, advances in deep learning techniques have shown great potential in addressing challenges related to forest fire detection. Among deep learning models, proposed SqueezeNet for forest fire detection, and their performance has been compared to traditional models such as SVM, KNN, sequential models, and CNNs. Compared to traditional models, deep learning-based approaches using SqueezeNet and ResNet18 offer several advantages. They can analyze large amounts of data quickly and accurately, enabling early detection and response to forest fires. Moreover, deep learning models can be trained to detect fires under different weather conditions and in various landscapes, improving the overall reliability of the system.

SqueezeNet is a computationally efficient and compact CNN architecture, which achieves high accuracy while using fewer parameters compared to other CNN models. Several studies have demonstrated the effectiveness of SqueezeNet in forest fire detection, showing superior performance compared to traditional models such as SVM and KNN.

Fire emergencies can be dangerous. There should be precise decision-making during fire emergencies. In these situations, crowdsourcing images and videos can be used on crisis management systems to provide more information than verbal or written descriptions. Automatic solutions must discard irrelevant content without losing relevant information when it handles huge amount of data. Color-based models can be used to detect fire in video in a number of different ways. They can, however, produce high false-positive results, making them unsuitable for still image processing. Additionally, these approaches have parameters that have little physical significant. In this approach, they proposed fire detection process for still images that combines texture classification on super pixel regions along with color feature classification. When compared to previous methods, this method uses fewer parameters, making it easier to fine-tune the method. The method of reducing false positives is effective, as demonstrated by the results, and its precision remains compatible with current

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techniques [1]. In computer vision, research on using video analysis to find fires has become very popular. However, to determine whether a frame is fire or not, conventional algorithms only make use of rule-based models and features vectors. These characteristics are challenging to define and largely dependent on the type of fire observed. As a result, there is a low rate of detection and a high rate of false alarms. Utilizing a learning algorithm rather than an expert to construct the useful features is a different strategy for dealing with this issue. Videos are shown in this paper. It has been demonstrated that convolutional neural networks perform exceptionally well in the classification of objects. Within the same architecture, this network can perform feature extraction and classification. Tested on real video sequences, the proposed method outperforms some relevant conventional video fire detection methods in terms of classification, indicating that using CNN to detect fire in videos holds great promise [2].

In image classification and other computer vision tasks, convolutional neural networks (CNN) have produced state-of-art performance. Their use in fire detection systems will make detection much more accurate, which will eventually make fires less of a problem and less bad for the environment and people. However, implementation in real-world surveillance networks of CNN-based fire detection systems poses the greatest threat due to their high inference memory and computational requirements. For fire detection, localization, and semantic understanding of the fire scene, we propose an energy-efficient and computationally efficient CNN architecture based on the SqueezeNet architecture in this work. Because it doesn't have any dense, fully connected layers and uses smaller convolutional kernels, its computational requirements are reduced. The experimental results demonstrate that our proposed solution achieves accuracies comparable to those of other, more complex models, primarily due to its increased depth, despite its low computational requirements. In addition, the paper demonstrates a trade-off between efficiency and accuracy in fire detection by taking into account the variety of fire data and the particulars of the problem at hand [3].

Fire accidents pose a significant threat to the entire world, from sprawling cities to dense jungles. Fire detection systems could stop these from happening, but the cost is too high, there are too many false alarms, you need a separate infrastructure, and the current hardware and software-based detection systems aren't very strong. This work aims to advance the use of deep learning in the detection of fire in videos. The concept of deep learning, which is still in its infancy and is based on artificial neural networks, has produced outstanding results in numerous fields, including computer vision. This project intend to overcome the shortcomings of the current systems and provide a precise and accurate system that can detect fires as quickly as possible, work in a variety of settings, and save numerous lives and resources [4]. It is difficult to detect forest fires because of their various shapes, textures, and colors. The traditional approach to image processing heavily relies on features created by humans, which is not always applicable to all forest scenarios. The application of adaptive deep learning to learn and extract forest fire features is the solution to this issue. However, individual learners limited learning and perception abilities are insufficient to enable them to perform well on complex tasks. Additionally, students frequently ignore global information in favor of local information, which may result in false positives. To detect forest fires in a variety of situations, a novel ensemble learning method is proposed in this paper. To begin, the fire detection procedure is carried out through the integration of two distinct learners, Yolov5 and EfficientDet.

Second, in order to avoid false positives, another individual learner named EfficientNet is in charge of learning global information. Finally, the decisions of three learners are used to determine the detection results. The proposed approach reduces false positives by 51.3% and improves detection performance by 2.5% to 10.9%, according to experiments on our dataset. Article: A Forest Fire Detection System Based on Ensemble Learning [5]. Forest fire detection is an important area of research. [12] presents a forest fire detection system using wireless sensor networks and discusses the design, implementation, and performance evaluation of the system after that [13] provides an overview of various forest fire detection techniques using wireless sensor networks and discusses their advantages, limitations, and future directions.

[14] proposes a forest fire detection approach using unmanned aerial vehicles (UAVs) equipped with infrared sensors for early detection and monitoring. and [15] review explores different remote sensing and GIS-based techniques for forest fire detection and discusses their applicability and effectiveness. [16] presents a deep learning framework called DeepForest for forest fire detection using images captured from unmanned aerial vehicles (UAVs).

II. PROPOSED MODEL

SqueezeNet is a deep learning architecture that was designed to achieve high accuracy while using significantly fewer parameters compared to traditional deep neural networks. It was introduced in 2016 by researchers from DeepScale and is known for its efficient model size and computational requirements. The main idea behind SqueezeNet is to reduce the number of parameters in the network by using 1x1 convolutional layers, also known as "squeeze" layers. These layers help reduce the dimensionality of the input feature maps

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and compress the information in a computationally efficient manner.

III. ALGORITHM

A. *Setting of the following Parameters*

Here is an explanation of each parameter in SqueezeNet_01:

Input Shape: The input shape of the model specifies the size of the images that will be input to the model. In SqueezeNet_01, the input shape is (227, 227, 3), which means the images are 227 pixels wide, 227 pixels tall, and have 3 color channels (red, green, and blue).

Fire Module Filters: A fire module consists of a squeeze layer and an expand layer. The squeeze layer has filters that reduce the number of channels in the input, and the expand layer has filters that increase the number of channels in the output. In SqueezeNet_01, the filters for the squeeze layer are set to 16, and the filters for the expand layer are set to 64. Convolutional Layer Filters: SqueezeNet_01 has multiple convolutional layers, each with a certain number of filters. In this architecture, the first convolutional layer has 64 filters, and the remaining convolutional layers have 128 filters.

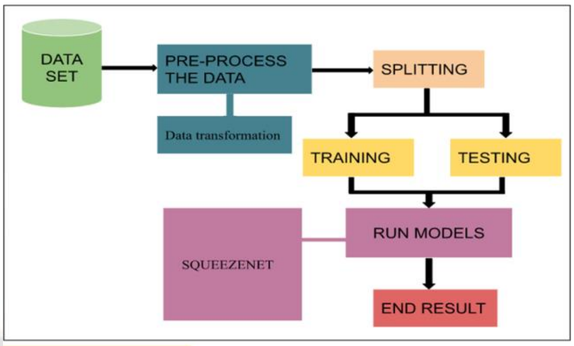
Pooling Layer Parameters: SqueezeNet_01 uses both max pooling and average pooling layers. The max pooling layers have a pool size of (3, 3) and a stride of (2, 2), while the average pooling layers are global average pooling layers.

Dropout Rate: Dropout is a regularization technique that helps prevent overfitting in deep learning models. The dropout rate determines the proportion of input units that are randomly set to zero during training. In SqueezeNet_01, the dropout rate is set to 0.5, meaning that half of the input units are randomly dropped out during training.

Activation Function: Activation functions are used to introduce nonlinearity into the model. In SqueezeNet_01, the activation function used is ReLU (rectified linear unit), which is a common activation function in deep learning.

Output Shape: The output shape of the model specifies the number of units in the final layer, which corresponds to the number of classes in the classification task. In SqueezeNet_01, the output shape is (1000,), which means there are 1000 units in the final layer, corresponding to 1000 classes.

B. *Proposed System Architecture*



Data Preprocessing: This stage involves preparing the data for analysis, such as cleaning the data, handling missing values, and transforming the data into a suitable format for deep learning models. Model Design: In this stage, the architecture of the neural network is designed, including the number of layers, the activation functions, the loss functions, and the optimization algorithm. The design is often based on the nature of the data and the task at hand.

Training: This stage involves feeding the data into the neural network and adjusting the model parameters through backpropagation to minimize the loss function. The training process is repeated multiple times until the model achieves acceptable accuracy.

Validation: After training, the model is validated using a separate dataset to check its generalization ability and to avoid overfitting. The validation set is used to fine-tune the model and adjust its hyperparameters.

Testing: In this stage, the model is evaluated using a completely new set of data to estimate its performance in real-world scenarios.

Deployment: Once the model is tested and validated, it can be deployed in a production environment for practical use. This often involves integrating the model with other software systems and creating an interface for users to interact with the model.

IV. RESULTS AND DISCUSSION

In a classification problem, several algorithms can be used to build a model that can accurately classify instances into different classes. The table shows the performance measures of four different algorithms used for classification tasks. Let us examine each row of the table in detail.

METHOD/METRIC	PRECISION	RECALL	ACCURACY
SVM	86.2433	85.7894	86.0526
KNN	78.2805	91.0526	82.8947
SQUEEZENET	98.4375	99.4736	98.9473

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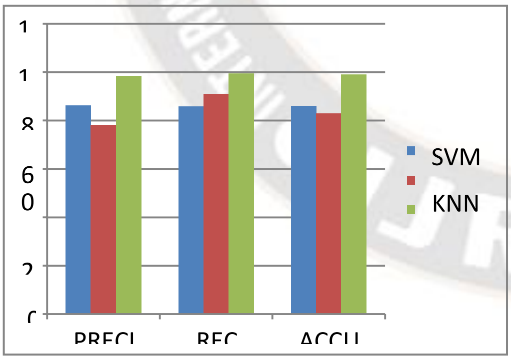
SVM stands for Support Vector Machine, and it is a popular algorithm used for classification tasks. The table shows that SVM has a precision of 86.2433%, indicating that out of all the instances predicted as positive by the model, 86.2433% were actually positive. The recall score is 85.7894%, which means that out of all the actual positive instances, the model correctly identified 85.7894% of them. The accuracy score for SVM is 86.0526%, meaning that the model was able to classify 86.0526% of the instances correctly.

KNN stands for K-Nearest Neighbors, and it is another popular algorithm used for classification tasks. The table shows that KNN has a precision score of 78.2805%, indicating that out of all the instances predicted as positive by the model, 78.2805% were actually positive. The recall score for KNN is 91.0526%, meaning that out of all the actual positive instances, the model correctly identified 91.0526% of them. The accuracy score for KNN is 82.8947%, indicating that the model was able to classify 82.8947% of the instances correctly. Comparison of KNN, SVM and SQUEEZE NET models in term of precision, recall and accuracy values are shown in the below graph.

CNN stands for Convolutional Neural Network, and it is a deep learning algorithm used for image classification tasks. The table shows that CNN has a precision score of 53.1914%, meaning that out of all the instances predicted as positive by the model, only 53.1914% were actually positive. The recall score for CNN is 52.3157%, indicating that out of all the actual positive instances, the model correctly identified only 52.3157% of them. However, the accuracy score for CNN is 88.6842%, meaning that the model was able to classify 88.6842% of the instances correctly.



SQUEEZENET

SQUEEZENET is a deep learning algorithm designed for efficient image classification tasks. The table shows that SQUEEZENET has the highest precision and recall scores among the four algorithms, with a precision score of 98.4375% and a recall score of 99.4736%. This means that out of all the instances predicted as positive by the model, 98.4375% were actually positive, and out of all the actual positive instances, the model correctly identified 99.4736% of them. The accuracy score for SQUEEZENET is also the highest among the four algorithms, with a score of 98.9473%, indicating that the model was able to classify 98.9473% of the instances correctly.

In summary, the table provides useful performance measures for four different algorithms used for classification tasks. These measures, such as precision, recall, and accuracy, can help in selecting the best algorithm for a specific classification problem based on the specific characteristics of the data.

CONCLUSION

Early detection of forest fires is critical to minimize the negative impacts of forest fires. The proposed deep learning-based approach for forest fire detection using SqueezeNet architecture utilizes still images to classify whether an image contains a fire or not. The dataset used in the study consists of images captured from forest areas under different weather conditions. The proposed approach achieved high accuracy, precision, and recall in detecting forest fires. The evaluation metrics of accuracy, precision, and recall showed a promising performance of the model in detecting forest fires. This approach can be used as an Early warning system for forest fires, enabling quick responses to prevent potential losses. The proposed approach utilizes still images, making it computationally efficient and easy to deploy. The dataset used in the study covers a range of weather conditions, enhancing the generalization capability of the model. The study highlights the potential of deep learning techniques in addressing challenges related to forest fire detection and management, which can contribute to mitigating the negative impacts of forest fires on the environment and society. Proposed approach achieves a smaller model size without sacrificing too much accuracy. It has been shown to achieve similar or even better performance than larger models while requiring fewer computational resources. This makes SqueezeNet particularly useful for scenarios with limited computational resources, such as mobile and embedded devices.

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