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TRANSFER LEARNING BASED FIRE RECOGNITION

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Abstract- Over the past decade, Researchers have been interested in fire detection because of the serious harm that may be done to both people and property in a short amount of time. Fire is harmful and widely contagious. Therefore, the response speed of fire-detection system critical. One of the modern explanations developed for fire-detection is using deep learning algorithms equipped with cameras to monitor and detect fires. Datasets are splitting (80%) for the training set and (20%) for the test set. The system was able to identify the fires using the collected data set. The deep learning transmission network algorithm (VGG16) obtained a classification accuracy of (99.27%) and the network algorithm method (VGG19) obtained the classification accuracy is up to (99.40%).

Keywords: FIRE, Deep Learning, Neural Networks, VGG19, Recognition.

1. INTRODUCTION

Fire is very contagious and dangerous. The fire can be averted and managed in its early stages. Early fire detection and suppression are required. As a result, the fire detection system's response time is crucial. The VGG19 a neural network that makes use of strong semantic traits to discriminate between picture classes. In order to train a model for quick fire picture identification, the input image size, and fully connected layer dimensions are decreased, high level semantic features and low-level texture qualities are taken into consideration, and a multi-layer feature fusion resolution is used [1]. One of the machine learning methods is the deep learning model. There are several layers in the input photo data and classification output herein type of artificial neural network. These layers extract important messages from the data using linear or nonlinear functions. Depending on their performance, layers can have several designs, including convolutional, pooling, and connected.

Since the 1980s, neural networks have been used in machine learning design. However, neural networks were not made using graphics processing units (GPU) until the early twenty-first century. The biggest impediment to the development of neural networks is the computing power needed. A Neural Network often has to be trained by repeatedly computing millions of parameters. The deeper the network, the more general the information that is learned. Each convolutional layer of a Deep Convolutional Neural Network (DCNN) collects features from the data and learns abstract information from it. The majority of current DL approaches employ network deepening to improve model fidelity. However, the deep web needs many data to operate at its best. Deepening networks may result in overload when there is a shortage of data. The goal of attaining generic traits will thus be unachievable [2].

Zbigniew Omiotek and Andrzej Kotera, in 2021, used a pre-trained VGG16 model to classify fire images. The VGG16 algorithm accurately detected specific combustion states ranging from 82% to 98% [3]. Jonardo, et al. clustering algorithm regression, random forest return, and regression with support vectors, and recurrent neural network (RNN) were four machine learning techniques that were employed in this study in 2021 to create a pattern identification model and visualize fire incidences throughout a county. Laguna, Philippines. They created a model to discover trends of fire incidences in Laguna Province, Philippines using a machine learning algorithm to anticipate and analyze fire data. The researchers used the data set to train the algorithm and divided it into a train set of 80% of the data and a test set of 20% of the data. Show RNN amazing result Retrieval with an overall mean of 0.98 with an overall mean of 0.982. The F-score had an overall mean of 0.98 [4]. Abdullah, et al. according to a study published in 2021, using IOT device fitted with security cameras are one of the most current methods created to detect fire. The network or IoT devices actually handle it. If the detection method necessitates computation, the latter scenario is necessary.

However, there is a disadvantage to using the cloud. In reality, using the cloud might make it look as though a threat file has violated a location's privacy through hacking or illegal access to snapshots of the location where the cloud is deployed. Study presents a fire alarm system with excellent accuracy while protecting the neighborhood's privacy. The system uses the cloud to identify fires; rather than transmitting real pictures, this is done by sending the characteristics derived from the Internet of things trick has collected to the cloud. Using a Convolutional Neural Network (CNN) to create an algorithm for detecting fires. CNN is employed for classification, whereas video descriptors are used for feature extraction.

Footage of actual fires and the usage of non-fire scenarios in this development. The outcomes demonstrate how well the proposal performed. The fire detection technique outperforms the most recent algorithms that use raw movies directly and can reach a classification accuracy of 97.5%. Therefore, the suggested fire detector is as trustworthy as existing devices on the market, with the added benefit of maintaining anonymity. Additionally, it has been demonstrated that a Raspberry Pi IoT device may be used to implement the suggested video descriptors for real-time processing [5].

Mounir Grari, et al. proposed a fire-detection system by means of a movie from 2022. that mimics the fire-detection procedure. recommended approach employs quicker convolutions based on area Neural networks to distinguish fire-prone and non-fire-prone areas created on spatial attributes. Following that, the features are compressed into bounding boxes in subsequent frames. It is constructed using good memory to quickly categorize whether or not there is a fire. Then, a choice for the following near term is added and a majority vote is used to determine the final decision for the long term. In order to assess dynamic fire behavior and make a final fire selection, its temporal variations are computed and Furthermore to the areas of flame and smoke, are presented. Tests demonstrate that compared to static or close-range images, the suggested long-term video-based system can increase the accuracy of fire detection. strategy employing video that reduces both false and inaccurate detection [6].

Jiaqi Wang and others Researchers employed the ResNet model in 2021, a deep learning transfer method that is effective in geometric deformation and can distinguish shifting patterns. In addition, it may generate more in-depth picture characteristics, avoiding optical flaws and conventionally difficult extraction computations. These tastes are intriguing. Pay attention to variations in the surface, form, color, and other characteristics of the smoke. Remaining depth, the performance of a convolutional neural network using the ResNet model improves as the number of network layers rises. The outcomes demonstrate that the residual network structure is straightforward, the deep convolutional neural network's performance degradation issue is resolved under extreme depth settings, and the classification performance is outstanding [7].

Ali, et al. researchers employed the VGG19 network algorithm to identify fires in 2022. The Fire dataset uses the Dataset, which consists of 1.900 color photos and 950 images. An effective categorization of forest fire photos versus fire is necessary for a powerful forest fire detection system. The effectiveness of several machine learning classifiers is then examined for the binary wildfire detection issue. In addition, we suggest a transfer learning approach based on VGG19 to boost prediction accuracy. Several machine learning methods, such as the Support vector machine, naive Bayes, random forest, and nearest neighbor, logistic regression, and the recommended method to properly identify between fire and non-fire photos, are evaluated and compared on the Fire dataset. The simulation results demonstrate how good the plan is at accurately classifying data, as it obtains an average accuracy of 95%, an accuracy of 95.7%, and a retrieval of 94.2% [8]. Chinese, et al. in 2020, researchers combined a transfer learning-based convolutional neural network with the TNVGG-19 fire recognition model. First, we train the feature extraction network using a learning transfer technique. Second, this work adds a newly created completely linked layer unit to the current VGG-19 model. We used the data augmentation approach since the flame data are part of a tiny sample. The learning strategies presented in this study can significantly increase the correctness of prediction and decrease the number of wrong alarms, according to experiments showing that the TNVGG-19 fire identification model is transport-dependent [9] [18].

This work aims to make a system that performs a portion of the functions that closed circuit television (CCTV) monitors fire. After performing the neural network training process, the proposed system detects fire using deep learning neural networks (VGG19) and network (VGG16) to detect fires, where the neural networks mentioned above are trained on a data set containing (4135) images divided into two groups, the first set being the training data set (80%) of the data, and the second set being Val/Test data (20%).

2. METHODOLOGY

The challenge might be solved by using a variety of object recognition and fire approaches to train the model. Using images of fire and others, not fire, we focus on using network (VGG19) and network (VGG19) to detect fire in a given image.

2.1. The Proposed System

1. Set up the system and transfer footage from camera.
2. Training networks to classify fire images.
3. Use VGG16-VGG19 networks to enter the target location.
4. Begin the classification model.
5. Detection of fire to reach the final effect.

In Figure 1, the system is shown in its entirety, where it begins by finding detects fire using deep learning neural networks (VGG19) and network (VGG16) method, which has been trained.

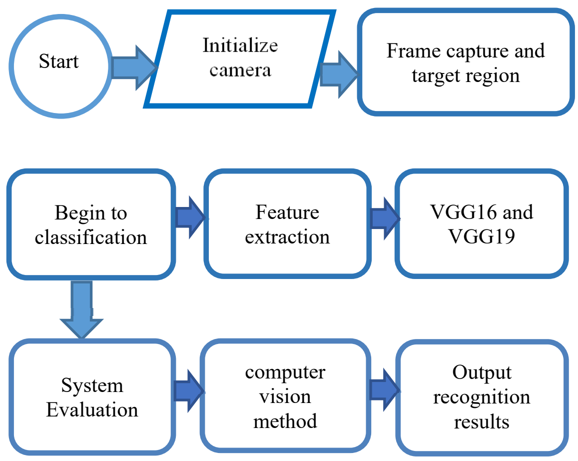

Figure 1. System fire recognition using the pre-training method

2.1. Fire Recognition

When the Recognition method is completed, the image is sent into the neural networks (VGG19) and network (VGG16) method for fire recognition. Convolutional Neural Networks (VGG16-VGG19) were trained using a fire image dataset.

2.2. Convolutional Neural Network (CNN)

Feed-forward for deep artificial neural networks, known as CNN [19], is mainly used in object identification and picture categorization. In 1989, Cun, et al. employed CNNs for the first time to detect handwritten zip codes; their algorithm could do so without the aid of or under the supervision of humans. A CNN output layer is composed only of connected layers, (Convolution, pooling operations). Most CNNs incorporate residual networks to prevent gradient decrease since the binary classification for the output layer is a sigmoid layer Some of those layers, though, may be applied to the network. Superior learning may be accomplished through a sizable network that enables self-organization and learning [13] [16].

2.3. VGG16

VGG16 contains an intense network with (16) CONV layers, consisting of two fully connected layers, a SoftMax classifier, and thirteen convolutional layers [11]. The VGG16 model has achieved the best performance, which is why it is being used. Convolutional and fully connected layers were produced using the VGG16 network. Only 3×3 For clarity, 3×3 conv layer was piled on top of one another. The VGG-16 shown in Fig 2.8 is as follows: 64 feature kernel filters with a 3×3 dimension makes up the 1 and 2 convolutional layers. The input picture, an RGB image with a depth of 3, changes in size as its transverses the first and second convolutional layers, becoming 224×224×64. Output is subsequently sent to the top pooling layer with a stride of 2. The 128 feature kernel filters for the 3 and 4 convolutional layers employ the 3×3 filter size. The output is decreased to 56×56×128 after these first two layers and a max pooling layer with stride 2. Stages 5, 6, and 7 employ convolutional layers with kernel sizes of 3×3. 256 feature maps are used in all three. The next layer is a stride two max pooling layer. Using 3×3 kernel sizes, there are two sets of convolutional layers. from 13th to 8th. In each convolutional layer set, the kernel filter is (512). Amax-pooling layer with a stride of 1 is the following layer. The 14 and 15 levels are entirely connected to 4096 units' hidden layers (16 layers). Figure 3 displays the Architecture of deep learning neural networks (VGG16) [12] [26].

2.4. VGG19

The photos were categorized into 1000 item groups, (2014) proposed the VGG19, a CNN comprising 19 layers, sixteen convolution layers, and three fully linked layers. The VGG19 algorithm is trained using the ImageNet dataset, which contains one million images organized into 1000 types. Conv-Layers are a widespread technique for classifying photographs since each layer uses several 33 filters. Figure 4 depicts the construction of the VGG19. This demonstrates that while the final three convolutional layers are used to classify, the first 16 convolutional layers are used to extract features. A max-pooling layer separates five sets of feature extraction layers. This model creates the label for the object in the image after receiving a 224×224 image. A pre-trained VGG19 model is utilized in the article to retrieve features, and additional machine-learning techniques are employed for categorization [14] [21].

3. EXPERIMENTAL SETUP

The following system components were installed on a laptop: An Intel Core I7 CPU from the 6th generation, 8 GB of RAM, and an internal display with Intel HD graphics 4600 resolution (2 GB).

3.1. Dataset

Used fire image data and an image dataset for a fire category. The model using VGG19 and VGG16 model the total amount of Dataset used to train the fire recognition algorithm (4135). eighty percent of the pictures were used as train data, while twenty percent were used as test/validation data (Table 1). Some of the data set's examples are shown in Figure 2. We randomly collected images of fire from various Mosul areas and another image from the internet; it is worth mentioning that the data includes a range of other license plates.

Table 1. Dataset Split

Type Dataset	No. Image	Percent
Training	3308	80%
validation	827	20%

Figure 2. Example of image dataset

3.2. Python Language and Parameters

The training model is designed using IDLE (python 3.7), and several hyper parameters are applied to all models. These are used to train each model, and the best results are retained for comparison and performance analysis of each model in the future, including:
Epoch: 100 - Image size 200×200 -Learning rate (α): 1e-4 - Optimizer: Adam and patch size is 32.

3.3. Precision

One of the measures is precision. This evaluation approach typically uses precision, defined as the proportion of truthfully predicted positive classes all items with a positive prediction, the precision show in Equation (1) [15] [20].

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

3.4. Recall

The ratio of *TP* and total of ground truth positives is described as the recall, usually referred to as the sensitivity or actual positive rate, of a specific class in classification the *Recall* show in Equation (2) [15][23].

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

The conflict between accuracy and recall; these two parameters are the two essential components in calculating the $F1$-score [24][28], which may be stated mathematically as follows:

$$F1 = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{3}$$

3.5. Model Training

Used the feature extractions to train the pre-trained Convolutional Neural Network (CNN) models [10][22], which leverages the ImageNet Dataset to import the weights of the pre-trained models (VGG16 and VGG19). To retrain the model for new classification tasks, the final completely connected layer with 1000 neurons was deleted and replaced with a fully connected layer with two neurons to categorize the necessary classes. The parameters of the frozen layers do not update during training, resulting in a fast rise in the model's training speed. In this case, Softmax was employed as an activation function.

Moreover, insert innovative layers afterward. This is accomplished by setting the upper layers to False. The model's last three layers are changed to adapt to the unique categorization task: Average Pooling, Dense FC with ReLU activation function (AF), Dense FC with Softmax function, and classification output layers. A pooling layer is added to increase feature extraction (FE) [24] performance. Additional FC layers are introduced to achieve classification using features learned from a new input set. In CNN, the AF ReLU is often used. CNN architecture has been utilized behind all convolution. The two models were then trained on (4135) photos of ambulances and trucks utilizing datasets for image recognition scores with two Classes. The image's input size is (200×200×3), and each model has a summary to evaluate layers and feature maps for correctness. Utilized a learning rate of (1e-4) and patch size classifiers (32) for a total of (100) epochs. The feature map is utilized as an input to a complete communication layer to get classification results. Despite outperforming the original convolutional neural network, this pre-trained model does not minimize overfitting. As a result, these models need image data optimization and parameter fine-tuning. Methodology of training model VGG16 and VGG19 model created a flowchart in Figure 3 that demonstrated a step-by-step training model using custom data.

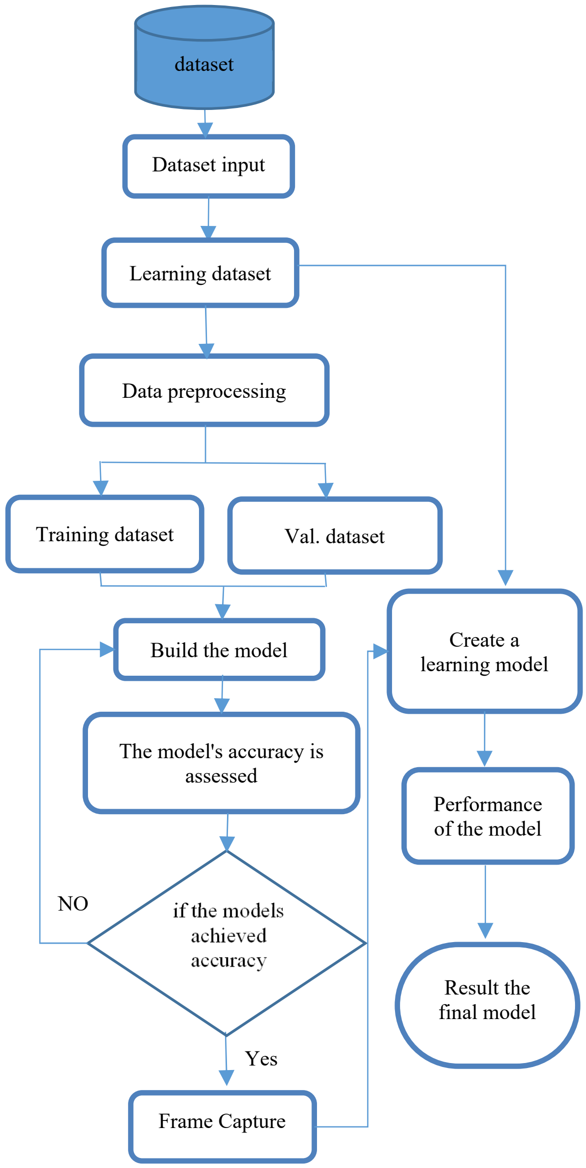

Figure 3. Training model on custom data system

4. RESULTS AND DISCUSSION

The model is trained on a custom dataset. Networks (VGG-16 and VGG19) were trained to Recognition fire by using two image recognition classes on (4135) images of fire image, and other the image input size is (200×200). Several hyperparameters are used in preparing the training model, keeping the best results for comparison and studying the performance of each model in the future.

4.1. Result of the VGG16 Model

Model VGG16 has been calculated for both training and validation samples at each epoch in which the model is trained. Figure 4 illustrates the efficiency for both validation and training samples. The accuracy curve for the VGG16 is depicted. It starts to grow with each epoch as training progresses until it is stable. We look at the data set's training curve to ensure its accuracy. Where it achieves an accuracy of up to 99.27%.

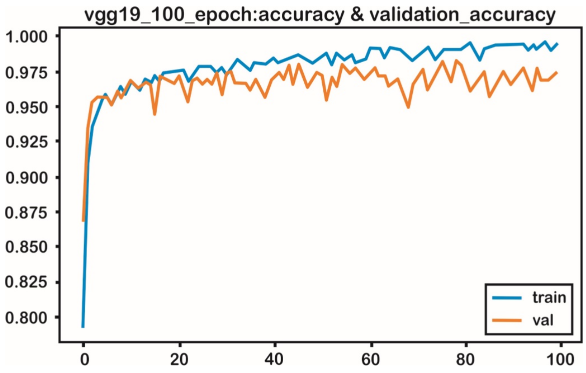

Figure 4. VGG16 accuracy curve

The loss curve for the VGG16 training model, the loss curve begins to decrease gradually after each training period, as we notice that the value of the training data fluctuates, the value of the loss curve for training data set to (0.0215) and the average loss value for the curve of the validation data set up to (0.1374). Figure 5 shows the loss curve during train and validation.

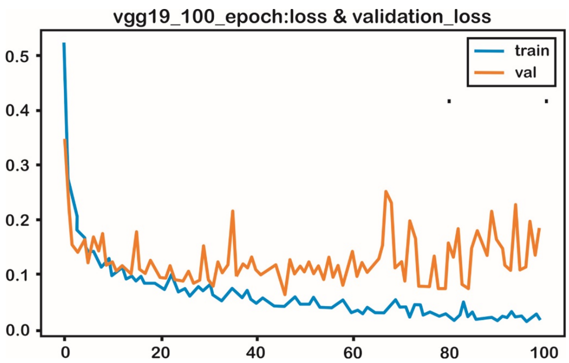

Figure 5. VGG16 loss curve

4.2. Result of the VGG19 Model

Model VGG19 has been calculated for both training and validation samples at each epoch in which the model is trained. Figure 6 illustrates the efficiency for both validation and training samples. The accuracy increases with the beginning of training, and the curve rises with each epoch. A look at the training curve of the data set to ensure its accuracy, after which the verification accuracy curve achieves accuracy up to 99.40 %.

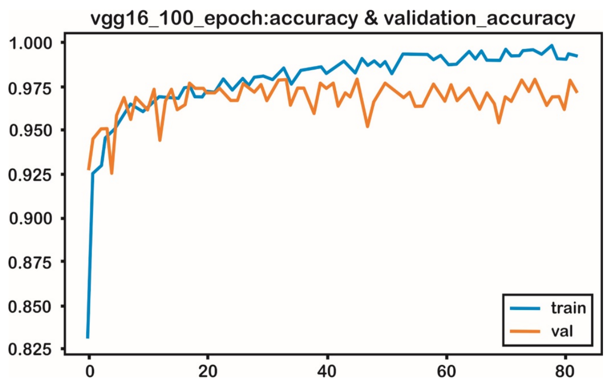

Figure 6. VGG19 accuracy curve

After each training session, the loss curve for the VGG16 model starts to decline progressively. We can see this by comparing the average loss value for the curve of the validation data set to (0.0160) and the loss value of the training data to (0.0160) (0.1827). The loss curve during train and validation is shown in Figure 7.

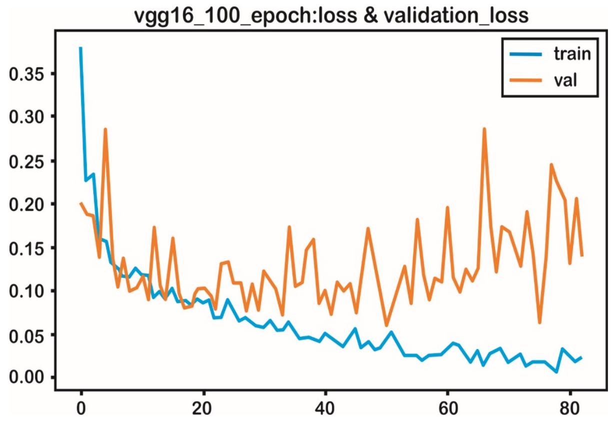

Figure 7. VGG19 loss curve

4.3. Experimental Results for Proposed System

The images shown in Figure 8 are specific to the fire Recognition system that will distinguish the fire. The results of the system are shown in the implementation window of the Python program.

```
display(Image('/content/drive/MyDrive/test_paper/fi
resize= tensorflow.image.resize(img1,(224,224))
y = img_to_array(resize)
x=py.expand_dims(y,axis=0)
val= model.predict(x)
print(val)
dic=["fire","nofire"]
result=argmax(val)
print(dic[result])
```

```
1/1 [==============================] - 0s 19ms/step
[[1. 0.]]
fire
```

Figure 8. Pictures from the system's work showing the work of detecting vehicle license plate numbers in the sample road

5. CONCLUSION

This paper deals with real-time fire recognition work which contains several different types and shapes of fire image. The images used in the dataset are accurate and good enough to fit the possibility of recognizing the fire, and this enabled us to obtain high accuracy in detecting and recognizing fires using the CNN algorithm to illustrate and evaluate efficiency. The increasing size of the network input layer (VGG16 -VGG19) will increase the image recognition accuracy but will reduce the recognition speed of images entering the network. The results show that training a network based on transference learning allows us to obtain an increase in accuracy and a lower training time instead of training the network from scratch. Better results will be obtained by increasing the number of model parameters, but this will also slow down the process of object characterization and detection. The findings demonstrate that, as opposed to starting from scratch, transfer learning-based network training enables us to increase accuracy while reducing training time, and that increasing the size of the network input layer (VGG16-VGG19) will increase image recognition accuracy while lowering image recognition speed that enters the network. The system was implemented based on deep learning and using CNN transfer learning architecture (VGG16 - VGG19) to identify fire with accuracy (99.23%) according to VGG16 network and with accuracy (99.40%) for VGG19 network networks were found to be the most successful in identifying fires in terms of accuracy and size. More work will be necessary to produce a new data set of larger size. However, it is better to use a dataset with different image orientations and lighting.

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