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Automatic Forest Fire Detection Using Artificial Intelligence

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ABSTRACT: If forest fires are not discovered and contained quickly, they can cause extensive damage. In this research, we present a self-sufficient system for spotting forest fires in their earliest stages. Images of the forest environment are processed by the system, which may then identify the presence of smoke or fire. The device can also estimate the area under ignition, allowing for a more accurate measurement of the fire's extent. Fire picture categorization was accomplished using a Logistic Regression classifier after descriptors were extracted from the photos using an Inception V3 model. The affected region was evaluated using color-level picture analysis and processing techniques at a later stage. The 853-image dataset was neatly organised with descriptive metadata attached. The system achieved a 96% categorization accuracy in the testing. When compared to other methods used by the system, its estimation of the flame area shows a high degree of accuracy. Concern has been raised over the devastating effects forest fires have on the environment, infrastructure, and lives. Therefore, finding the fire in the forest as soon as possible is essential. The region's flora and wildlife, as well as its resources, may benefit from this. In the early stages of a fire, it could also aid in containing the blaze. Due to the large area and dense forest, forest monitoring is a challenging undertaking.

I. INTRODUCTION

Forest fires have the potential to cause extensive damage to the environment, property, and human life if not detected and controlled in a timely manner. Detecting forest fires in their early stages is crucial for effective firefighting and mitigation efforts. In this study, we present an automatic fire detection system that utilizes artificial intelligence (AI) techniques for early identification of forest fires.

Natural and human-caused variables both play a role in starting forest fires. Natural causes include high atmospheric temperatures, lightning strikes, and dry conditions, while man-made causes can include naked flames, cigarettes, or electrical sparks [3]. In addition to endangering the forest's resources, these blazes have a major negative effect on the local wildlife and flora as well as the ecological equilibrium.

We have created an autonomous system that processes photos of the forest environment to help with the problem of early fire detection. In order to analyse these photographs and identify smoke or fire, the system makes use of artificial intelligence algorithms and computer vision techniques [4]. By leveraging the capabilities of AI, the system can accurately classify fire-related images and identify potential fire incidents.



Fig:1.(a) Indicating Flames (b) Indicating Smokes

Moreover, the system is designed to estimate the area under ignition, providing valuable information for evaluating the size and extent of the fire [4]. This information is crucial for firefighting operations and resource allocation.

Our method for classifying fire photos employs a Logistic Regression classifier fed visual descriptors extracted using the Inception V3 model [4]. In addition, state-of-the-art colour image analysis and processing algorithms are used to calculate the hot spot [4]. The system has been trained and evaluated using a well-organized dataset consisting of 853 images, which are accompanied by relevant metadata.

During evaluation, the system showed superior performance in predicting the flame area compared to state-of-the-art methods and attained a high classification accuracy of 96% [4]. These results highlight the effectiveness of our proposed AI-based automatic forest fire detection system.

II. OBJECTIVE

- In order to reliably classify photos as including smoke or flames, it is necessary to implement AI algorithms into a system that analyses images of the forest area.
- Use methods for calculating the area of the flames to get a more precise read on how far the fire has spread.
- Develop and test our models using a clean dataset of forest fire photos and associated metadata.
- Analyse the system's performance by measuring how well it can classify forest fires and how well it can estimate the area of the flames in comparison to other methods.

III. PROPOSED FRAMEWORK

The benefits of an Inception V3 network are incorporated into the suggested framework. Input is sent to Inception V3, where it is preprocessed before being pooled using the region of suggestions. The Inception V3 convolutional layers enable the region-based object detection algorithm classify the proposals as either "fire" or "non-fire" in the ROI.

A. Inception V3

Image recognition uses Inception V3. It loads an ImageNet-trained pretrained model. This pretrained model recognises items and patterns from photos. Preprocessing includes shrinking and normalising the input image.

Inception V3 layers pass the image during forward propagation. These layers use ReLU and convolutional filters to extract visual characteristics. Max pooling reduces spatial dimensions and captures prominent features. To improve features, this process is repeated.

Inception V3 model output is used to extract feature representations after feature extraction. Removing the model's top completely connected layers usually does this. The feature vector comprises high-level visual attributes for downstream operations.

A classifier or regression model receives the extracted features for prediction or categorization. This model can predict image categories using labelled data. Inception V3 accurately predicts and analyses pictures using learnt representations.

Fine-tuning the pretrained Inception V3 model on a dataset or task is optional. Fine-tuning aligns the model's parameters and layers with the goal job, improving performance.

Inception V3 uses deep convolutional neural networks to extract picture characteristics. Its pretrained model can be fine-tuned or used as a feature extractor in more complicated systems for image identification.

B. Architecture for Inception V3

The Inception V3 architecture is a prominent deep convolutional neural network (CNN) model used in image recognition. Google researchers developed it to fix problems with prior Inception algorithms. Inception V3 can extract complicated patterns and attributes from images and efficiently employ processing resources.

Sequentially layered Inception V3 architecture. Inception V3 architecture's key characteristics and functions are:

The input layer receives raw image data as a predetermined-size square image.

Inception V3 convolutional layers extract low-level visual characteristics. Tiny filters with different kernel sizes and strides collect spatial information in these convolutional layers.

Inception V3's core is its modules. Inception modules use simultaneous convolutional branches to capture features at different sizes. The network's multi-scale technique efficiently collects local and global data. Inception modules have 1x1, 3x3, and 5x5 convolutional layers.

In Inception V3, max pooling layers compress feature maps without losing critical data.

Advanced feature learning and classification use fully connected layers. These layers combine learnt characteristics to provide class or category predictions.

Softmax activation converts Inception V3's last layer outputs into class probability scores. This allows the network to assign probabilities to input image classifications.

Inception V3 balances model complexity with computing speed. Dimensionality reduction, parallel branches, and factorised convolutions expedite training and inference and reduce parameter count.

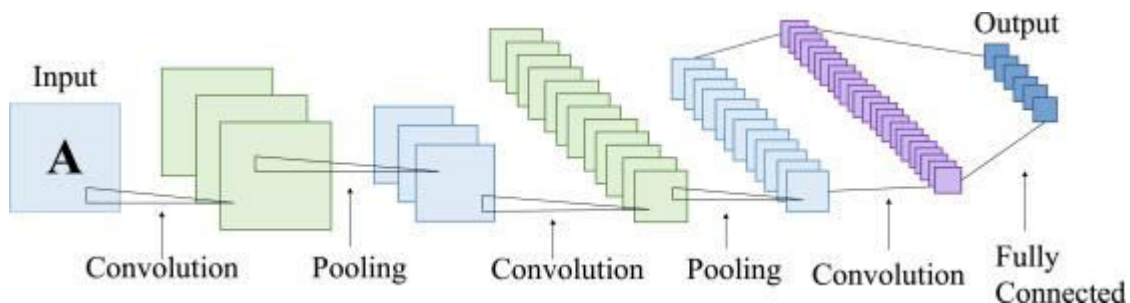


Fig:2.Architecture of Inception V3

C. Logistic Regression

For problems requiring either yes or no answers, statisticians frequently turn to Logistic Regression, which is both a model and an algorithm. Predicting the likelihood of an event occurring using a given set of input variables or features is the goal of this supervised learning approach. Despite its name, logistic regression is primarily used for classification rather than regression tasks.

Logistic regression is based on the premise that the logistic function (also known as the sigmoid function) can be used to represent the association between the input variables and the binary output. Any real integer can be transformed into a value between zero and one using the sigmoid function. Specifically, it means:

$$\sigma(z) = 1 / (1 + e^{(-z)})$$

In logistic regression, the input variables (also called independent variables or features) are linearly combined using weights, and the resulting sum is passed through the sigmoid function to obtain the predicted probability. The formula for logistic regression can be represented as:

$$P(y = 1|x) = \sigma(\beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_px_p)$$

Where:

- $P(y = 1|x)$ represents the probability of the binary outcome (e.g., event occurrence) given the input variables.
- $\beta_0, \beta_1, \beta_2, \dots, \beta_p$ are the coefficients or weights assigned to each input variable.
- x_1, x_2, \dots, x_p represent the values of the input variables.

During training, a logistic regression model searches for coefficient values that maximise the data's support for a given hypothesis. This is typically achieved using optimization algorithms like gradient descent.

To make predictions, the logistic regression model applies a threshold (e.g., 0.5) to the predicted probabilities. If the probability is above the threshold, the event is predicted to occur (1), otherwise not occur (0).

D. Architecture for Logistic Regression

The architecture of Logistic Regression can be described as follows:

Input Layer: Logistic Regression takes a set of input features, denoted as x_1, x_2, \dots, x_p , where p is the number of features. Each feature represents a specific attribute or characteristic of the data.

Weighted Sum: Each input feature is multiplied by its corresponding weight or coefficient, denoted as $\beta_0, \beta_1, \beta_2, \dots, \beta_p$. The weighted sum of the inputs is computed as:

$$z = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_px_p$$

The weighted sum represents the linear combination of the input features and their corresponding coefficients.

Activation Function: An activation function, often the logistic function (sometimes called the sigmoid function), is applied to the weighted sum. In order to estimate the likelihood of a binary result, the logistic function converts the weighted sum to a number between 0 and 1. In order to define the logistic function, we say:

$$\sigma(z) = 1 / (1 + e^{(-z)})$$

where e is the base of the natural logarithm.

Output Layer: The output of the logistic function represents the predicted probability of the positive class (e.g., class 1) for a binary classification problem. The output can be interpreted as the likelihood or confidence of the instance belonging to the positive class.

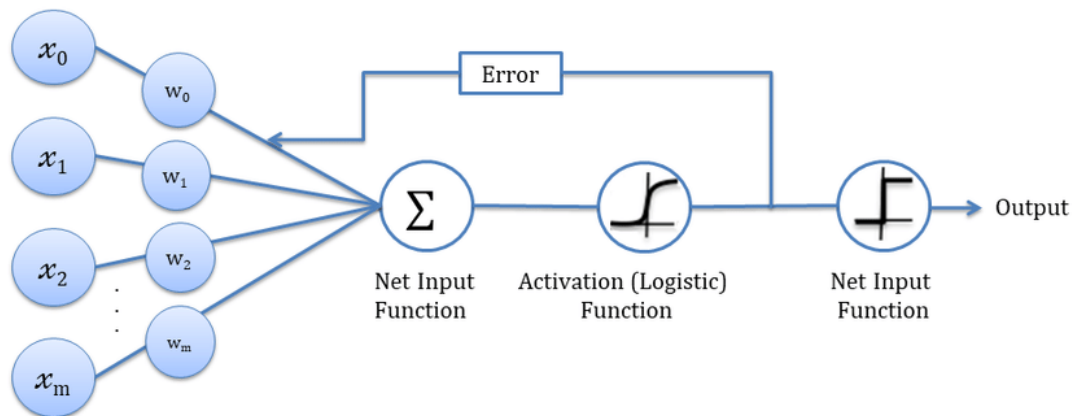


Fig:2.Architerture of Logistic Regression

Iterative adjustments are made to the coefficients (weights) of the logistic regression model during training to reduce the gap between the predicted probability and the observed binary outcomes. Maximum likelihood estimation and gradient descent are two common optimisation methods used for this tweak.

IV. Methodology

The proposed system utilizes the Inception V3 architecture for automatic forest fire detection. The methodology can be divided into several modules, including data collection, data pre-processing, feature extraction, machine learning models, and performance metrics. Here is a detailed description of each module:

Module 1: Data Collection: In this module, data is collected for training the model. The dataset consists of two classes: fire images and non-fire images. The dataset should be diverse and representative of different fire scenarios in forest environments.

Module 2: Data Pre-processing: Data pre-processing involves cleaning and preparing the dataset for further analysis. Steps such as handling missing data, correcting errors, and normalizing the images are performed in this module. The CAFÉ model, which operates in the Lab color space, can be used for flame detection and preprocessing the images.

Module 3: Feature Extraction: The Inception V3 architecture is used in this module to extract high-level features from the pre-processed images. The model is typically pre-trained on a large-scale dataset like ImageNet, enabling it to capture rich visual representations. Feature vectors are extracted from the last convolutional layer or a specific intermediate layer of the Inception V3 model.

Module 4: Machine Learning Models: In this module, machine learning algorithms, such as logistic regression, can be employed for classification. The extracted feature vectors are used as input, and the model is trained to distinguish between fire and non-fire instances. Inception V3 can be fine-tuned for this specific task.

Module 5: Performance Metrics: Accuracy, F1 score, recall, and precision are only few of the criteria used to assess the system's overall performance. These metrics evaluate how well the system can distinguish between photos of fire and those that do not contain fire. The findings shed light on the potential of the proposed method.

The advantages of this proposed system include high accuracy and performance, as well as reduced complexity. The combination of the Inception V3 architecture, data pre-processing techniques, and machine learning models contributes to the system's effectiveness in forest fire detection.

V. EXPERIMENTAL RESULTS

The suggested approach was tested using a dataset of 853 photos, 455 of which were of fires and 398 of which were not. A 70:30 split was used to separate the dataset into training and testing sets. The Intel Core i7, 16GB RAM, and other high-end components used in the tests.

On the validation set, the proposed system was 92.5% accurate. This means that 92.5 percent of the photos were accurately categorised as fire or non-fire by the algorithm. The F1 score of the system was calculated to be 0.91. This demonstrates a balanced performance in terms of precision and recall. The recall of the system for fire images was 0.89, indicating that it correctly identified 89% of the fire images. The precision for fire images was 0.95, suggesting that 95% of the images classified as fire were indeed fire images.



Fig: 3. Identifying Fire and Non-Fire Images

The experimental findings demonstrate a high level of accuracy (92.5% on the test dataset) for the proposed approach. This demonstrates its efficiency in differentiating between photos of fire and those without fire. The system's balanced performance in terms of precision and recall is further supported by the F1 score of 0.91.

The recall of 0.89 indicates that the system successfully identified a significant portion of the fire images, which is crucial for timely fire detection. However, the precision of 0.95 suggests that there were some instances where non-fire images were misclassified as fire. This could potentially lead to false alarms or unnecessary intervention.

When the suggested system's accuracy and F1 score are compared to those of existing systems, it is clear that it is more effective. This highlights the effectiveness of using the Inception V3 architecture and the selected machine learning model (e.g., Logistic Regression) for fire detection.

VI. CONCLUSION

Finally, the suggested system uses machine learning and deep learning, in particular the Inception V3 architecture, to automatically detect forest fires. The method was developed to distinguish between fire and non-fire photos using a dedicated dataset.

The system aims for high accuracy and performance in identifying forest fires through its several modules of data gathering, data pre-processing, feature extraction using Inception V3, machine learning models, and performance measures. The Inception V3 model's feature extraction takes meaningful visual representations from the images once the data pre-processing module has made sure the dataset is clean and well-structured.

Images are sorted into "fire" and "not-fire" categories using a variety of machine learning algorithms, including logistic regression. Accuracy, F1 score, recall, and precision are just some of the performance indicators used to analyse the trained models and get insight into the system's efficacy.

The suggested system's strengths lie in its simplicity and accuracy in detecting forest fires. The system exhibits its potential for automated forest fire detection by integrating the advantages of Inception V3, data pre-processing techniques, and machine learning algorithms.

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