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Forest Fire and Wild Animal Detection System Using Deep Learning

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Abstract: Fire outbreak is the common issue happening everywhere and the damage caused by this type of incidents is tremendous towards nature and human. Vision based fire detection system have recently gained popularity as compared to traditional sensor-based fire detection system. However, the detection process by image processing technique is very tedious.

We proposed a fire detection algorithm using Convolutional Neural Networks (CNN) to achieve high-accuracy fire image detection, trained on a dataset consisting of 3696 fire and 541 non-fire images, totaling 4237 images. Out of these, 2857 images were used for training and 1921 for testing. The model employs convolution, activation functions, and max pooling operations. Through experimentation with different batch sizes and epoch values, we achieved a model accuracy of 94%, correctly predicting 1817 out of 1921 test images.

Our study also reviews smoke and fire detection techniques, emphasizing early detection's importance. We discuss various methods, including RGB and HSI models, aiming to minimize false alarms through optimized technologies.

Furthermore, we address human-animal conflicts in forest zones by developing a monitoring system using cameras to detect intrusions, classify them, and notify relevant authorities.

I. INTRODUCTION

Fire detection is critical for public safety, but traditional sensor-based methods have limitations, mainly being confined to indoor environments and requiring specific conditions to activate. Video-based systems offer broader coverage and faster response times, leveraging existing surveillance infrastructure. However, reliable early detection methods are still lacking, posing risks of disasters. This paper explores various smoke and fire detection techniques, emphasizing image processing for open environments like ports and power plants.

Convolutional Neural Networks (CNNs) show promise for tasks like tree species classification from aerial imagery and wildlife monitoring via camera traps. The escalating human-wildlife conflicts, exacerbated by habitat encroachment and forest fires, underscore the need for intelligent monitoring solutions.

A network-based wireless sensor system for forest fire detection aims not only to alert individuals but also to mitigate loss of life and property. Moreover, automated tools like computer vision offer efficient and predictable data gathering, especially in challenging terrains like forests or deserts

II. LITERATURE SURVEY

1.Content-based Retrieval and Real Time Detection from Video Sequences Acquired by Surveillance Systems

Abstract: This paper introduces a surveillance system designed to detect abandoned objects in unattended environments, augmented with image processing content-based retrieval capabilities to facilitate operator inspection tasks.

Methodology: Video-based surveillance systems typically utilize one or more cameras linked to monitors. These systems rely on human operators to interpret acquired information and monitor events in surveyed environments. Recent efforts have focused on developing systems that assist human operators by drawing attention to unusual situations.

Conclusion: Experimental results demonstrate the probability of correctly detecting abandoned objects, along with examples of retrieval sequences**.**

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2.Image Processing based Forest Monitoring and Counteracting System Wildfire

Abstract: Forests cover one-third of Earth's land, providing essential resources for sustaining life. However, forest degradation has escalated in recent decades.

Methodology: This system offers continuous live data on forest environmental conditions. It aids in detecting fire intensity, facilitating water discharge for extinguishing fires during unfavorable conditions.

Conclusion: The system enables rapid response by activating submersible pumps to disperse water from nearby tanks based on sensor node feedback.

3.Forest Fire Prediction Using Machine Learning Techniques

Abstract: Forest fire prediction is vital for effective fire control, addressing a significant environmental challenge that leads to ecological destruction, disrupts ecosystems, increases the risk of natural hazards, and contributes to global warming and water pollution.

Methodology: Utilizing random forest regression and hyperparameter tuning via the Randomized Search CV algorithm, we employed various dataset sub-samples to fit decision trees and improve predictive accuracy while mitigating overfitting.

Conclusion: Our study demonstrates that Randomized Search CV coefficient calculation with hyperparameter tuning yields optimal results, with Mean Absolute Error (MAE) of 0.03, Mean Squared Error (MSE) of 0.004, and Root Mean Squared Error (RMSR) of 0.07.

4.Robust Real-Time Periodic Motion Detection

Abstract: We present novel techniques for detecting and analyzing periodic motion captured by both static and moving cameras. By tracking objects of interest, we compute their self-similarity as they evolve over time. For periodic motion, the self-similarity measure exhibits periodicity, and we employ Time-Frequency analysis to identify and characterize this motion.

Methodology: Our approach relies on two key assumptions: 1) segmented objects' orientation and apparent size remain relatively constant over several periods, or change periodically; 2) the frame rate sufficiently captures the periodic motion (at least double the highest frequency present).

Conclusion: We robustly analyze periodicity using 2D lattice structures inherent in similarity matrices. Future research aims to explore alternative independent motion algorithms for moving camera footage, enhancing robustness for nonhomogeneous backgrounds in such scenarios

5.Motion Detection for Security Surveillance

Abstract: This paper presents the design and implementation of a Smart Surveillance Monitoring System utilizing Raspberry Pi and CCTV cameras, with Python software as a pivotal component. The system addresses the necessity for motion detection in modern times.

Methodology: The setup includes Raspberry Pi Model B, memory, an LCD display screen, a DC servo motor, CCTV camera, and power supply. The power supply connects to Raspberry Pi, which interfaces with the DC servo motor. Continuous development in surveillance systems addresses security concerns, necessitating more accurate and automated solutions.

Conclusion: The project envisions addressing obstacle detection, including ground and airborne objects like aircraft. The system's primary objective is to detect obstacles and capture images on a computer. The camera interfaces with the BCM2835 processor on the Pi via the CSI bus, facilitating high-bandwidth transmission of pixel data.

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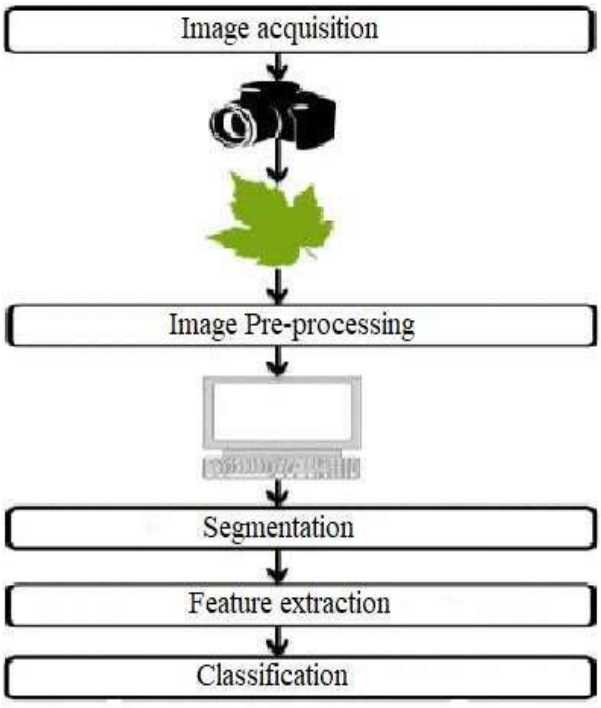
III. PROPOSED SYSTEM

- The proposed system includes five modules. The initial stage is the image acquisition stage through which the real-world sample is recorded in its digital form using a digital camera.
- In the next stage of the research image was subjected to a pre-processing stage. Making use of it the size and complexity of the image is reduced.
- The precise digital information is subjected to segmentation process which separates the rotten portion of the Animal samples.
- The feature extraction aspect of an image analysis focuses on identifying inherent features of the objects present within an image.
- Classification maps the data into specific groups or classes.



High-level design (HLD) explains the architecture that would be used for developing a software product. The architecture diagram provides an overview of an entire system, identifying the main components that would be developed for the product and their interfaces. The HLD uses possibly nontechnical to mildly technical terms that should be understandable to the administrators of the system. In contrast low level design further exposes the logical detailed design of each of these elements for programmers

High level design is the design which is used to design the software related requirements. In this chapter complete system design is generated and shows how the modules, sub modules and the flow of the data between them are done and are integrated. It consists of very simple phases and shows the implementation process.

The proposed system has the following steps for smoke and fire detection
i. Image Pre-Processing
ii. Identification
iii. Feature Extraction
iv. Fire and Smoke Detection

Image Pre-processing: The image processing is a mechanism that focuses on the manipulation of images in different ways in order to enhance the image quality. Images are taken as the input and output for image processing techniques. It is the analysis of image-to-image transformation which is used for the enhancement of image. Firstly, we convert RGB image to gray scale image. It helps to reduce the complexity in the image and also make the work easy. Then by using min-max scalar method converts the gray scale values into binary values.

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The obtained binary values are taken as the input for the further process. In the obtained binary matrix consider one value regions as white and zero value region black. By using these values, the region of interest can be identified. So that the values are useful for feature extraction and identification of region of interest

Identification: In this stage identify the region which needs to proceed for further process, it is involved in the identification of the region of the image that is used for the further process like feature extraction and classification of the images. The output of the pre-processing step is given as the input for the identification process. This process is based on the binary values obtained in the pre- processing step. The region with black are consider as region of interest. The region of interest obtained by the pre-processing of the images. That region is considered as proceeding part of the image from which smoke and fire will be identified. The identified smoke and fire images are given to the feature extraction process.

Feature Extraction: In this stage extract the required feature from the identified region which are obtained from the previous step. That region is compressed by converting reduced size matrix to control over fitting. The reduction of the matrix size helps in reduce the memory size of the images. Then the flattening process is applied to the reduced matrix, in which the reduced matrix is converted to one-dimension array, which is used for final detection.

Fire Detection: This methodology proposes utilizing a Convolutional Neural Network (CNN) model for fire detection. Image datasets are constructed from fire images extracted from videos and supplemented with images sourced from the internet. The dataset comprises 2,316 fire images and 541 non-fire images, totaling 2,857 images. These images are resized to (300,300) and reshaped as (-1,300,300,1) to form a linear array input for the convolutional layer.

The model consists of 64 convolution filters of size 3x3 each, followed by ReLU activation to update positive portions of feature maps rapidly. Feature maps then undergo max pooling. This process is repeated with another convolution and pooling layer with a 3x3 kernel size. A flatten layer converts 2D feature maps into a vector for the fully connected layer.

During training, weights of neurons in the convolution and fully connected layers are learned and adjusted for better data representation. A dense layer performs matrix-vector multiplication, with trainable parameters updated during backpropagation, yielding an m-dimensional vector as output. The SoftMax activation function is used in the final layer to classify outputs as fire or non-fire, providing a probability distribution ranging from 0 to 1.

The model is compiled using an Adam optimizer for adaptive learning rates and categorical cross-entropy loss function for classification, as only one result can be correct.

System Architecture:

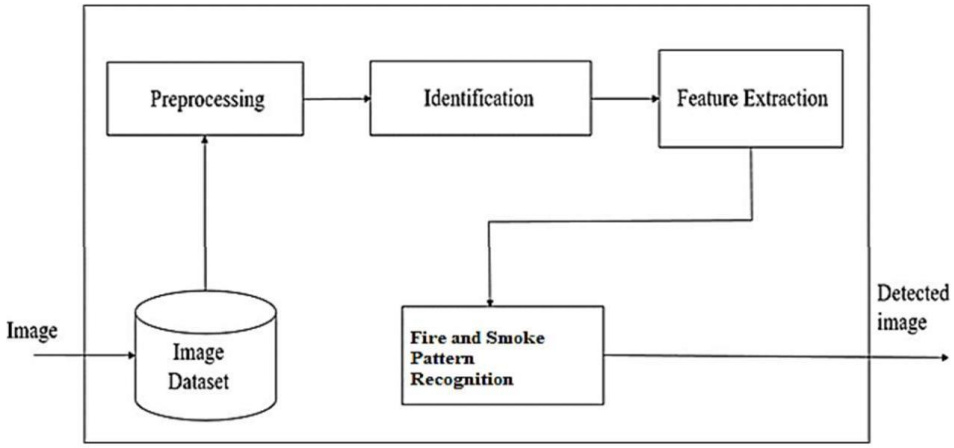

Fig: System Architecture of the smoke and Fire detection

The figure shows the system architecture for the proposed system. The input image is pre- processed and converted to gray scale image to get the clear vision of the image. Then it will be converted into binary values. In the next step identifies the part which needs to proceed further. Then required feature are extracted by In the CNN convolution layer.

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By passing those features into different layer of CNN we get compressed image, that feature is used for detection of smoke and fire using SoftMax activation function.

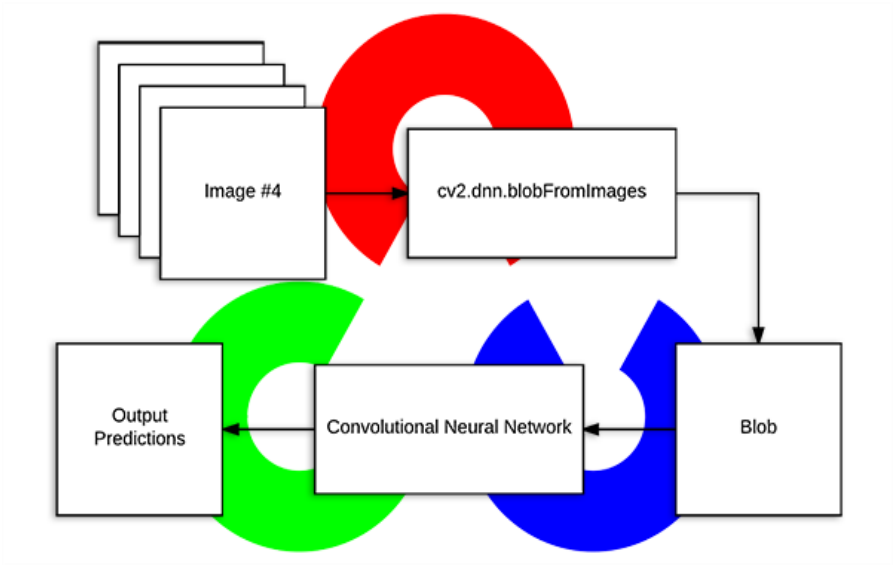

Fig : System Architecture of the Animal detection

OpenCV provides two functions to facilitate image preprocessing for deep learning classification:

- cv2.dnn.blobFromImage
- cv2.dnn.blobFromImages

These two functions perform:

- Scaling
- Mean subtraction

Before we even begin training our deep neural network, we first compute the average pixel intensity across all images in the training set for each of the red, green and blue channels.

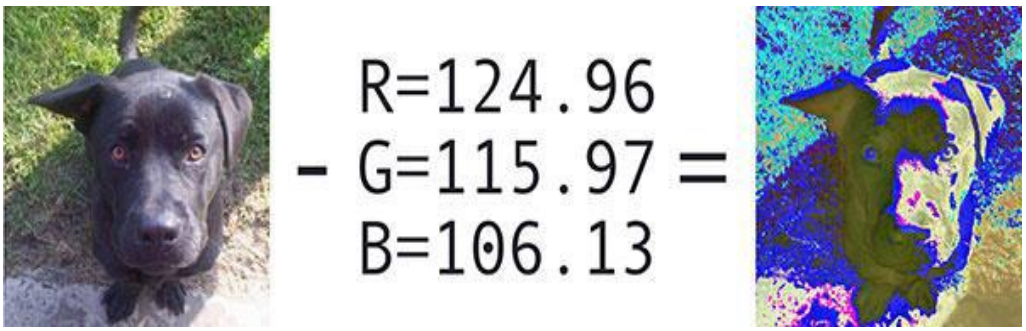

Fig: Mean Subtraction

Before we dive into an explanation of OpenCV's deep learning preprocessing functions, we first need to understand mean subtraction. Mean subtraction is used to help combat illumination changes in the input images in our dataset. We can therefore view mean subtraction as a technique used to aid our Convolutional Neural Networks.

Specifications using Use Case Diagrams: A use case diagram at its simplest is a representation of a user's interaction with the system that shows the relationship between the user and the different use cases in which the user is involved. A use case diagram can identify the different types of users of a system and the different use cases and will often be accompanied by other types of diagrams as well. While a use case itself might drill into a lot of detail about every possibility, a use case diagram can help provide a higher-level view of the system. It has been said before that "Use case

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diagrams are the blueprints for your system". They provide the simplified and graphical representation of what the system must actually do.

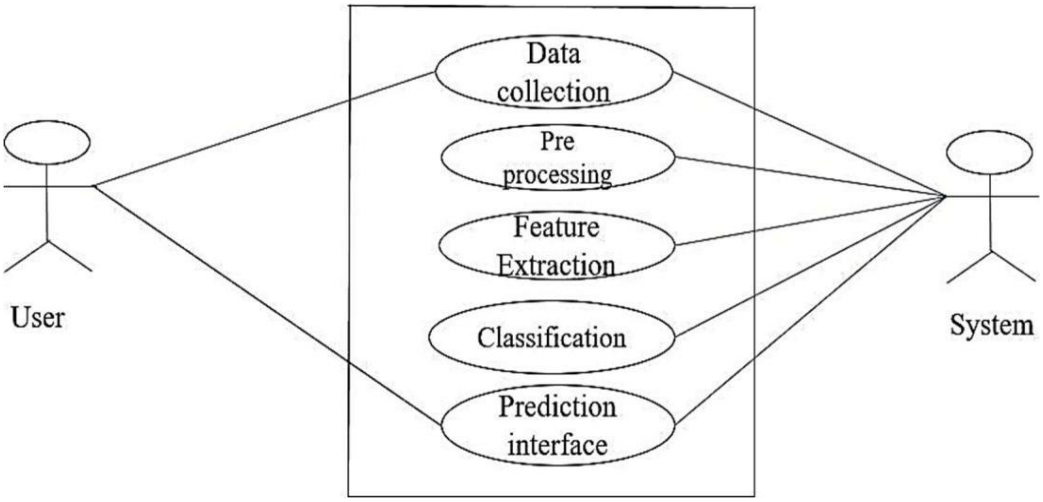
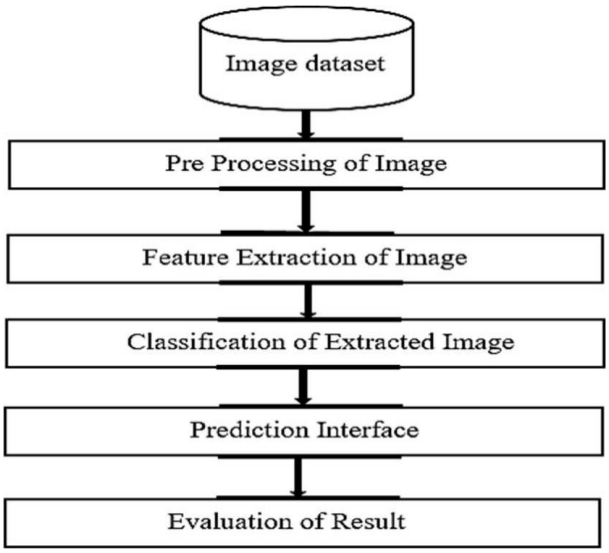


Fig : Use Case Diagram

System Implementation:



Convolutional Neural Network (CNN): CNNs are a type of deep neural network inspired by the visual cortex, designed for analyzing visual imagery. They find applications in image and video recognition, image classification, and natural language processing.

The first layer in a CNN is the convolutional layer, which extracts features from input images. This layer preserves pixel relationships by learning image features using small squares of input data, known as filters or kernels. Each input image passes through multiple convolution layers with filters to generate output feature maps.

In essence, CNNs operate by passing input images through convolution layers with filters, enabling the extraction of relevant features for tasks like image recognition and classification

Convolutional Layer: In the convolutional layer, the computer reads an image in pixel form and applies small patches called filters or features. These filters are compared to different areas of the input image by lining them up and multiplying corresponding pixels. The resulting values are added up and divided by the total number of pixels in the filter. This

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process creates a map where the filter values correspond to specific positions. By moving the filter across the entire image, we obtain a matrix output, indicating how well the filter matches different areas. This approach allows the convolutional layer to identify similarities and classify images based on these features

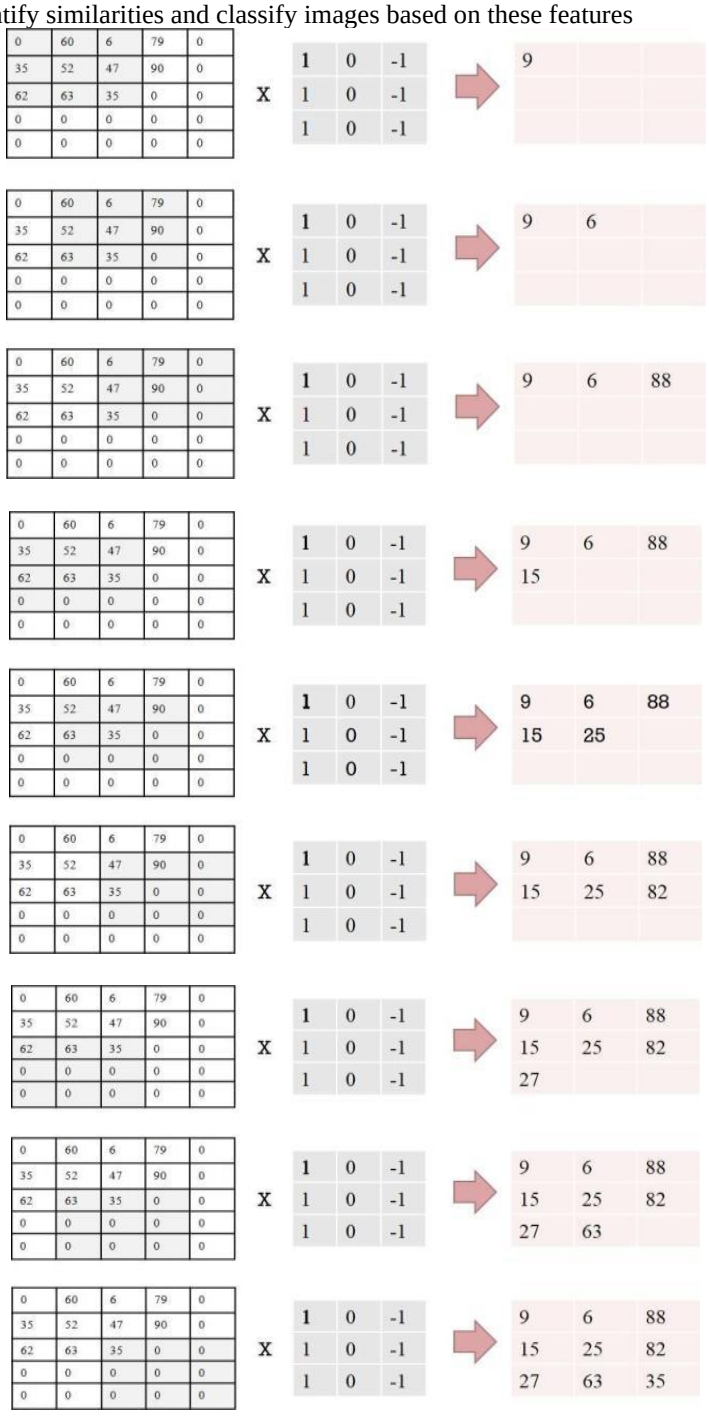

Fig : Convolutional Layer

ReLU Layer: ReLU layer is nothing but the rectified linear unit, in this layer we remove every negative value from the filtered images and replaces it with zero. This is done to avoid the values from summing up to zeroes. This is a transform function which activates a node only if the input value is above a certain number while the input is below zero the output will be zero then remove all the negative values from the matrix.

Pooling Layer: In this layer we reduce or shrink the size of the image. Here first we pick a window size, then mention the required stride, then walk your window across your filtered images. Then from each window take the maximum

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values. This will pool the layers and shrink the size of the image as well as the matrix. The reduced size matrix is given as the input to the fully connected layer.

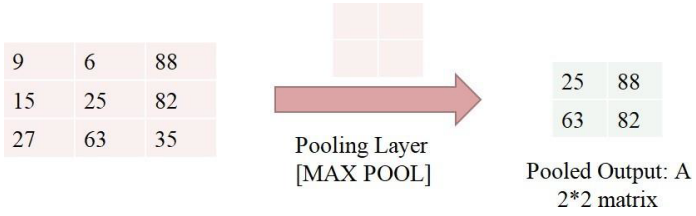
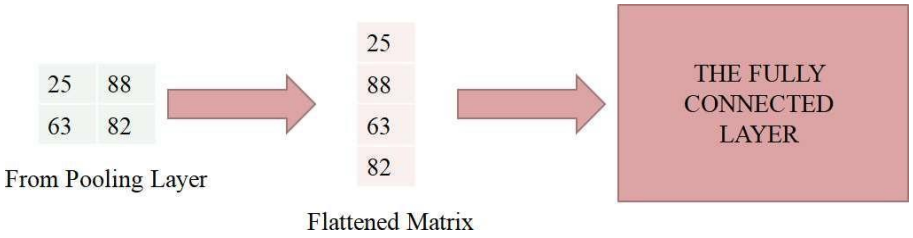


Fig : Pooling Layer

Fully Connected Layer and Output Layer: We need to stack up all the layers after passing it through the convolutional layer, ReLU layer and the pooling layer. The fully connected layer used for the classification of the input image. These layers need to be repeated if needed unless you get a 2x2 matrix. Then at the end the fully connected layer is used where the actual classification happens.



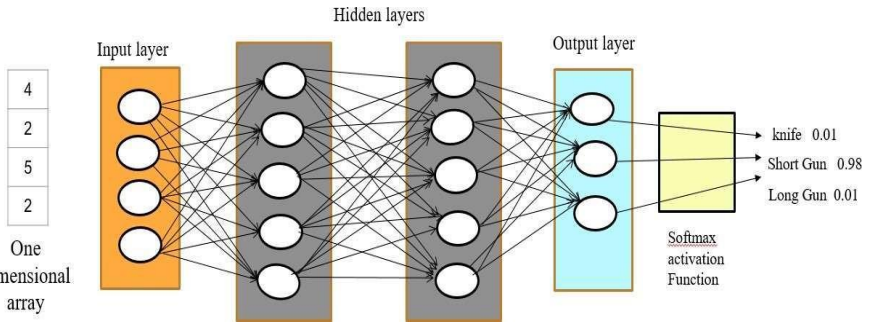


Fig : Fully Connected Layer and Output Layer

The embedded system software is written to perform a specific function. It is typically written in a high- level format and then compiled down to provide code that can be lodged within a non-volatile memory within the hardware. An embedded system software is designed to keep in view of the three limits:

- Availability of system memory
- Availability of processor's speed
- When the system runs continuously, there is a need tolimit power dissipation for events like stop, run and wake up.

System requirements:

System requirement specifications gathered by extracting the appropriate information to implement the system. It is the elaborative conditions which the system need to attain. Moreover, the SRS delivers a complete knowledge of the system to understand what this project is going to achieve without any constraints on how to achieve this goal. This SRS not providing the information to outside characters but it hides the plan and gives little implementation details.

Specific Requirement:

- Require access to a client session of Python and Keras toolbox for job submission.
- A shared file system between user desktops and cluster.
- Maximum of Python worker per physical CPU core.

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Hardware Requirement:

- Laptop with Windows or Linux OS
- Camera

Software Requirement:

- OpenCV
- Python 3.7
- Python IDE 2

IV. RESULT

The User Interface (UI) of the proposed model is given below figure

Fig 4: User Interface Before any Button is Pressed

There are 3 different buttons used for activating the particular detection models

- 1st Button: To activate “Forest Fire and Smoke Detection” model.
- 2nd Button: To activate “Wild Animal Detection” model.
- 3rd Button: To activate “Domestic Animal Detection” model.

Forest Fire Detection:

In this we detect forest fire and smoke with the help of in-built web-camera of the laptop. It also produces alert sound and messages when it is detected along with confidence level in real time. The below figure shows the UI when this model button is pressed.

Fig : When 1st Button is Pressed

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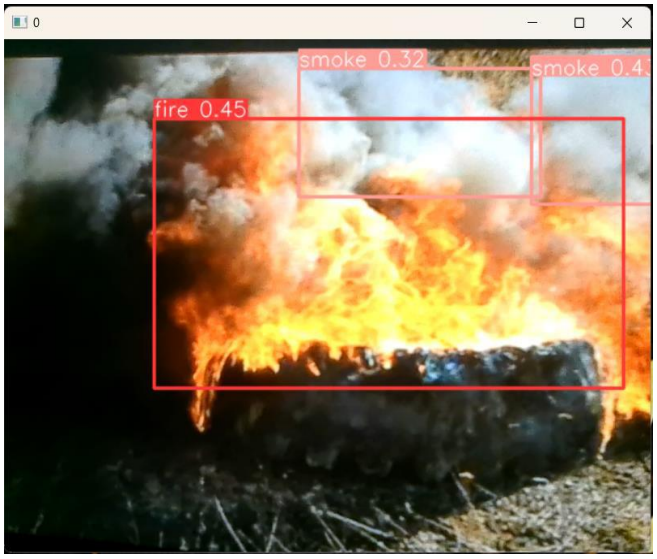

Fig : Real Time Detection of Fire and Smoke with Confidence Level

Fig 4.1.3: Alert Messages when Fire and Smoke are Detected

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Animal Detection

In this we detect wild and domestic animals with the help of in-built web-camera of the laptop. It also produces alert sound and messages when it is detected along with confidence level in real time. The below figure shows the UI when this model button is pressed.

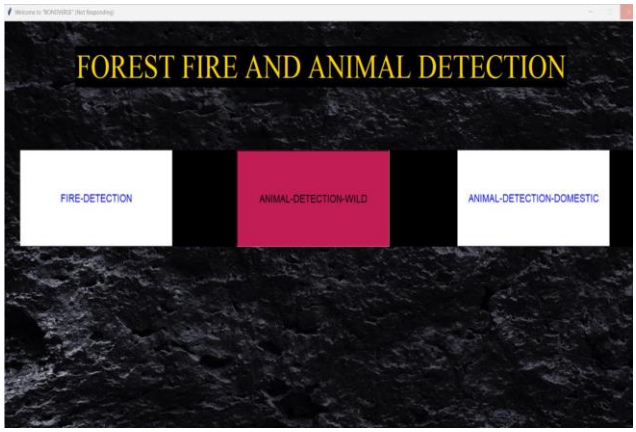

Fig : When 2nd Button is Pressed

Fig : Real Time Detection of Wild Animal with Confidence Level

Fig : Alert Messages when Wild Animals are Detected

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Fig : When 3rd Button is Pressed

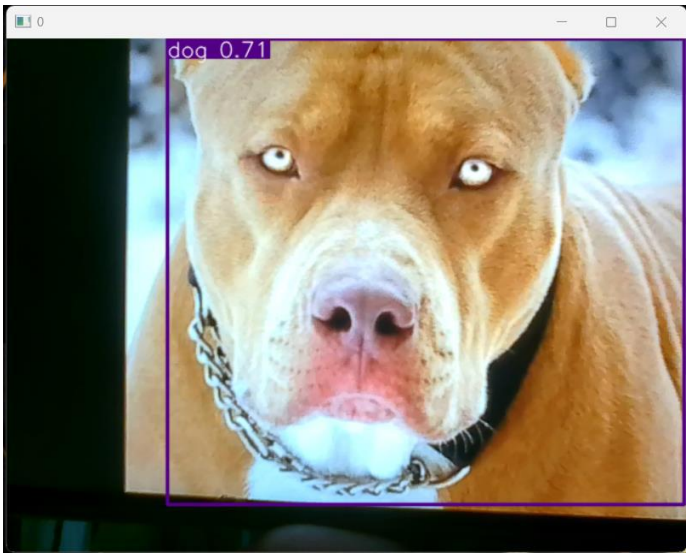

Fig : Real Time Detection of Domestic Animal with Confidence Level

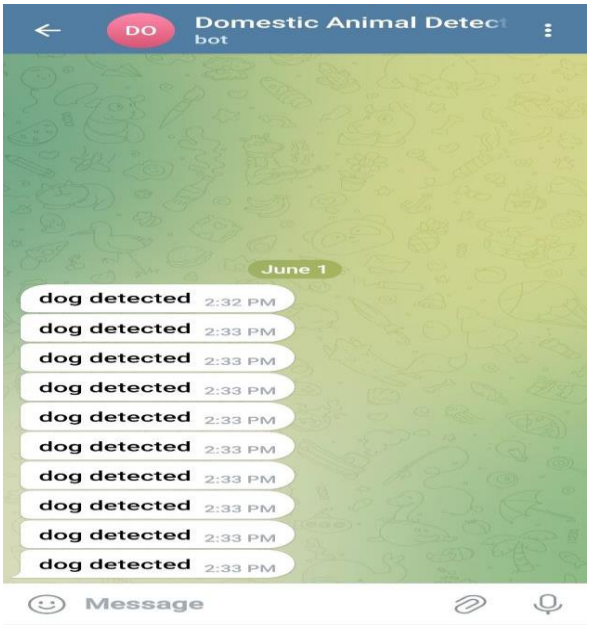

Fig : Alert Messages when Domestic Animals are Detected

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V. CONCLUSION

As a result of our literature review, we are able to determine that it is possible for us to build a powerful system to detect the fire and smoke with good precision and accuracy. This system can be used in forest offices to get alerts based on the threat of fire in the forest.

In this project the training data is taken as huge number of images so that the system learns to classify them depending on the presence or absence of fire and/or smoke. Here the system processes the image containing fire and smoke based on RGB to grayscale conversion process. We used three CNN techniques namely LeNet-5, AlexNet, VGG-16. The forest predictor developed, was trained, and tested on all of the 3 models mentioned above and it was observed that the predictor produced a better accuracy in the LeNet 5 when compared to the rest of the models.

The proposed forest fire detection technique is based on CNN. The algorithm takes a raw dataset and reshapes it according to the given specifications after which it trains the CNN model. When the images to be predicted are given to the trained model, an output as to whether the image contains forest fire or not is identified.

In future this project may be extended and implemented not only for detecting fire and smoke but also for identifying different weapons used to cut trees and hunt animals, to detect illegal tree cutting and hunting, to detect animals that are crossing forest area and dwell into human society. We can even make the user choose what activities he/she needs and provide just those applications in the system according to their requirements. We can even make it available to defense units to detect suspicious activities in the forest.

The animals, many of which are already threatened or endangered, are often killed in retaliation or to prevent future conflicts. So this zone is to be monitored continuously to prevent entry of wild animals. With regard to this problem, proposed system is developed which will monitor the field using camera and captured image of the intruder will be classified using image processing so that suitable action can be taken.

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