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Detection of animal intrusion using CNN and image processing

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Abstract

One of the greatest dangers to agricultural productivity is animal damage to agriculture. Crop raiding has become one of the most antagonistic human-wildlife conflicts as cultivated land has expanded into previous wildlife habitat. Farmers in India endures major risks from pests, natural disasters, and animal damage, all of which result in lesser yields. Traditional farming methods are unsuccessful and hiring guards to watch crops and keep animals at bay is not a practical solution. It is critical to protect crops from animal damage while also redirecting the animal without injuring it, as the safety of both animals and people is essential. To get over these obstacles and accomplish our goal, we employ the deep learning concept of convolutional neural networks, a subfield of computer vision, to identify animals as they enter our farm. The primary goal of this project is to constantly monitor the entire farm using a camera that records the surroundings at all hours of the day. We identify animal infiltration using a CNN algorithm and Xgboost and notify farmers when this occurs.

Keywords: CNN; XG Boost; Computer vision; Deep learning

1. Introduction

In India, agriculture plays a key role. In India, agriculture has always been a major contributor to the country's GDP. The majority of Indians find work in agriculture, yet this sector is filled with challenges. Animal-human conflict has long been a big problem that has wasted countless resources and put people's lives in danger. In recent years, there has been an increase in the frequency of these sorts of conflicts. Therefore, this area needs continual surveillance to deter the introduction of such animals and other undesirables. Encroachment and poaching lead to human-animal conflicts because people go into the forest for subsistence, claiming land for agricultural practises and fast industrialisation leads the growth of urban ground, while animals approach surrounding villages in search of water during the dry summer months. Elephants and wild boars often trample agricultural plants in their hunt for food. When one species needs something, it might threaten the survival of another, depleting resources and sometimes claiming lives. South Asia and Africa are the most common regions where people and elephants come into conflict with one another. In most cases, an electric fence is used to keep animals out of a farm's crops. The address situations the animals to act in an odd manner, making them easier to capture. Deep learning strategies are required to avoid these types of issues. Researchers used various machine learning strategies similar to the Support Vector Machine (SVM) and Artificial Neural Networks (ANN) to help farmers overcome their ordeal and improve accuracy in identifying plant diseases. During the last decades, the risk of agricultural farms being accidentally damaged or defiled during routine animal intrusion has increased dramatically over the years. Animal research has been an vital field for applications with image processing like wildlife conservation and early warning systems for human intrusion into animal territory. Many algorithms and methods have been developed to enhance knowledge on ethology. Detection, tracking and identification of the animal can be narrowed down to the three main branches of these applications.

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On the other hand, the precision of such systems is heavily reliant on feature selection methodologies. With the elimination of image pre-processing and the facilitation of intrinsic feature selection, convolutional neural networks have recently made significant progress in automated image recognition. The availability of a large enough dataset for such competitions is another problem. In situations when there is a lack of data, it is best to utilise a model that has already been trained on a big dataset. Transfer learning is used to develop a model that is then fine-tuned to adapt the final layers to make them unique to the dataset at reference.

However, the precision of such systems is significantly influenced by feature selection procedures. Convolutional neural networks (CNNs) are a kind of neural network that significantly improves image-based recognition by doing away with the need for picture pre-processing and allowing intrinsic feature selection. Another difficulty is acquiring a large dataset sufficient for these contests. When the dataset size is limited, it is better to use a model that has been pre-trained on a large dataset. This is known as Transfer Learning. The dataset was developed to help with animal spotting using information gathered over the course of many months. Various animal images are used for the detection of the intrusion in farming fields, for the training the model.

1.1. Convolutional neural

1.1.1. Network

One kind of ANN is the convolutional neural network (CNN). Since it is optimised for handling data in pixel format, it may be used for image recognition and processing. It has multiple layers to process the data and extract important features from the grid like arrangement.

CNN saves a lot of time and also reduces errors. Since, it doesn't need more parameters for learning the characteristics of image filters. The main purpose of the CNN algorithm is to extract image features without losing the data it represents. CNN is based on neuroscience findings and is made up of artificial neurons.

Usually for image processing through CNN, if an image is given then it takes pixel values as data and picks some visual features. It points out the pixel values of colors for the activation function.

At initial stage it takes the edges of the picture and sends it to detecting the corners and color groups of the image. Then the image defined is passed to the next layer for pooling, this cycle continues until the image is predicted.

The decreased size of the image gives finite definition which makes RoI pooling occur. It only reveals the most relevant features for activation function features for dense process.

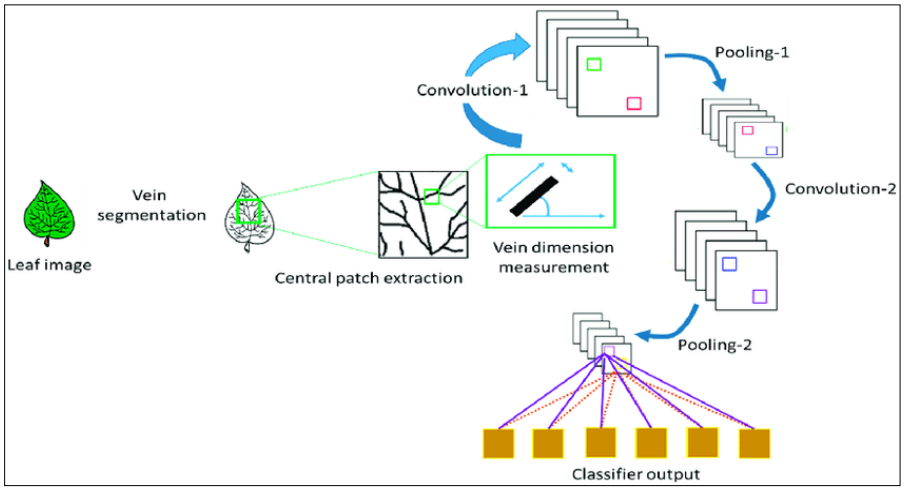

Figure 1 CNN model

Objectives

The goal of the project is to give security against wild animal attacks, ultimately decreasing the farmer's potential loss.

- Detecting intrusions in the field.

- Capturing the intruder's image and identifying it using image processing.
- Contrasting the image with an image of an animal.
- Taking appropriate response based on the type of intrusion.

2. Literature review

There is some related work that apply deep learning methodology for detection of animal intrusion such as Prakash, Banupriya[1] they describe a focused literature about the algorithm that classifies based on their image, so we can effectively guide them. Animal detection and classification may assist to avoid the accidents, track animals and prevent theft. Nagaraju Andavarapu and Valli Kumari Vatsavayi[2] it states that WCoHOG is a Histogram oriented gradient based feature vector with improved accuracy. It is an expansion of Co-occurrence Histograms of Oriented Gradients (CoHOG). LIBLINEAR classifier is used in order to get better accuracy for large dimensional data.

S. Yadahalli, A. Parmar and A. Deshpande [3] Here various sensors and cameras are interfaced with the board such as Passive Infrared Sensors (PIR), the camera capture the intruding image with TFT display. Gyanendra K. Verma and Pragya Gupta [4] The multilayer graph cut in the spatial-temporal domain was applied to a camera-trap database including prospective animal suggestions. These are put to use in the verification stage, which determines whether or not a particular patch represents an animal.

3. Proposed model

The proposed system consists of algorithms which are used in detecting animal intrusion in human lands and alerting the farmer when the intrusion occurs. Based on the CNN classifier, here the database for animals are collected and trained for predicting the intrusion. Two stage CNN with binary and multiclass level are used for the classification and feature extraction. Here, make use of LBP comprehension and XGBoost count, which provides the join mastermind by a large area of interest comprising both target animals and other false positive targets. A two stage flow is proposed for the high rate results regardless of less time and enormous usage. RoI pooling is considered for the multiple object detection in a single image.

The entire process can be divided into four modules such as

- Training images
- Data augmentation
- CNN classification
- Prediction and Alert

3.1. Training images

The training images is done to obtain the images of animals and train the own database set. By this the animals which intruded into farming fields are detected through cameras located on the fields. Here various animals which are common for the field intrusion are considered such as deer, cows, wild boar, elephants, monkeys etc. Kaggle is used for downloading image dataset for detection of animal intrusion.

3.2. Data augmentation

Using a process called data augmentation, fresh training data may be produced from existing data. It helps prevent machine learning models from being overfit during training by acting as a regularizer. Here in animal intrusion detection large datasets are considered for training as such the data augmentation leads to better prediction accuracy. While the process is operating, it has no effect on the size of the test sample. Data augmentation uses the techniques such as position, scaling, cropping, padding, brightness etc., by these the diversity of data within available is increased. Here data augmentation is performed for the animal image data training and prediction.

3.3. CNN classification

Convolutional neural network (CNN) classification is a form of deep neural network used for image classification and computer vision applications. CNN's key benefit over its forerunners is that it can recognise key traits automatically, without human intervention. Convolutional neural networks (ConvNets) are both more effective and less asset than traditional methods for machine learning. Here two stage CNN is used such as binary level classifier and multi-level

classifier. It is a supervised learning model which can differentiate various objects sizes, color in a single image. Return of Image pooling with XGboost is performed for the animal intrusion detection.

3.4. Prediction and alert

The number of the animal's types to be predicted are of approximately 20 with the image instances of 300 with various angles for testing. The classified output saves the human time and alert the farmer of the intrusion and also the cost damage caused to the field through intrusion of such animal. The immediate alert will reduce the damage rate to minimum. The prediction is performed by image testing through deep learning classifiers.

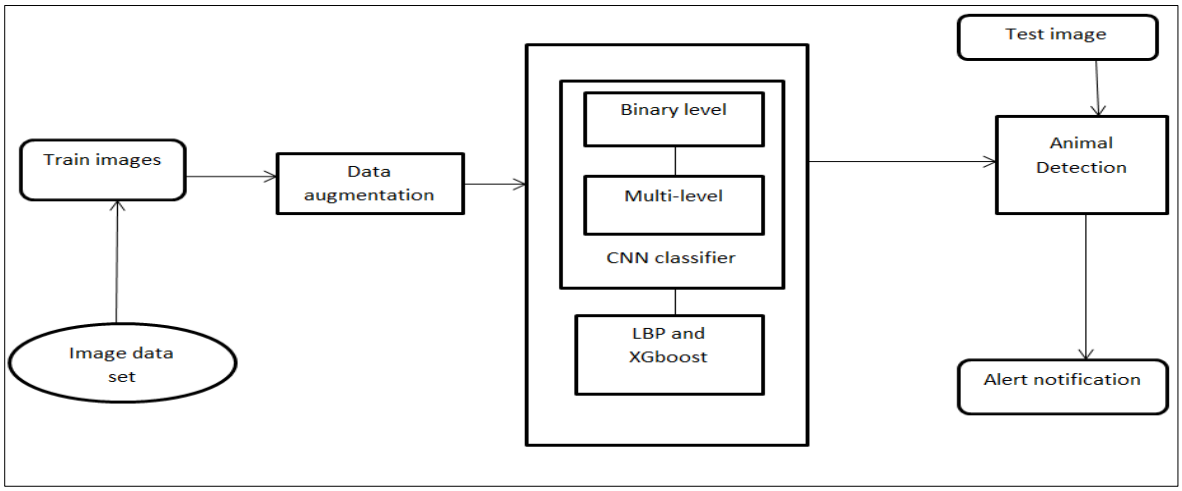

Figure 2 Architecture model of proposed system

3.5. Algorithm

3.5.1. Multipart CNN classifier

A CNN has numerous layers. When these layers are utilised multiple times, they result in a Deep Neural Network's path of action. There are three basic types of layers used to construct a CNN:

- Information: This layer contains the image's incorrect pixel estimations.
- Convolutional Layer: This layer receives the results of the neuron layer, which is linked to the data district. In this layer, we illustrate the degree of wreckage. Each channel may be a 5x5 window that slides through the data and selects the pixel with the highest striking power as the yield.
- Modified Linear Unit [ReLU] Layer: This layer handles picture data in a region-wise manner. We like that a CNN employs back increase. Designers use the ReLU work to maintain proportional estimations of the pixels while not being affected by the back starting.
- Pooling Layer: This layer performs a down-testing work along the spatial estimations (width, stature) in order to achieve volume.
- Totally Connected Layer: This layer is utilised to select the score classes, i.e. which class has the best score when compared to the data digits.

3.5.2. LBP

To assign labels to picture pixels, Local Binary Pattern (LBP) thresholds the area around each pixel and treats the output as a binary number. To extract hierarchical data representations, deep learning is widely used. The Local Binary Pattern Network (LBPNet) is presented as a means of efficiently collecting and comparing high-level over-complete features in a multilayer hierarchy.

For the LBP, we first determine the LBP code for each pixel and then build a histogram of those LBP codes to use as the LBP feature. Assigning a value of 1 to a neighbouring pixel x if and only if that pixel is also a neighbour of pixel p, the central pixel's 8 neighbours are compared with pixel p.

3.5.3. XGBoost

XGBoost is an efficient and dependable gradient boosting solution that stretches the boundaries of processing power for boosted tree algorithms, with the primary goal of enhancing the efficiency and effectiveness of machine learning models.

Steps involved in the processing of XGBoost are

- Step 1: Load all libraries
- Step 2: Load the dataset
- Step 3: Data Cleaning and Feature Engineering
- Step 4: Fine-tune and run the model
- Step 5: Evaluate the Test Population

XGBoost's objective function is the product of a loss function assessed over all predictions and a regularisation function for all predictors (j trees). A prediction from the jth tree, denoted by fj in the formula.

$$\text{obj}(\theta) = \sum_{i}^{n} l\left(y_i - \hat{y_i}\right) + \sum_{j=1}^{j} \Omega(f_i)$$

Log loss is a popular measure that is used by XGBoost. Use this probability-based measure to evaluate a classification model's efficacy.

$$-\frac{1}{n}\sum_{i=1}^{N} y_i . \log\left(p(y_i)\right) + (1 - y_i) . \log(1 - p(y_i))$$

Constructed trees and models are used to get all of the potential solutions to the equation F2(x) = (0+1*h1(x)+1*h2(x)), where the final value of F2(x) is the XgBoost model prediction, if we are interested in creating a prediction for a new data point.

4. Results

Our model has been trained by using Multistage CNN with LBP histograms and XGBoost gradient. Login page and registration page is created for the farmers for registering their details and when the animal is detected of intrusion in the farming fields. The mail and alert notification is sent to the farmer. The Kaggle website is used for the image dataset for detecting animal intrusion. The MySQL is used for the details storage of users and Tkinter is used as its frontend.

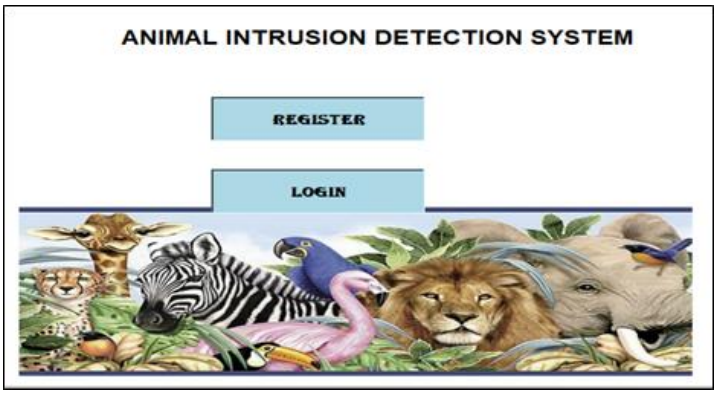

Figure 3 Home page

The registration page and login page is of

Figure 4 Registration page

Figure 5 Login page

And result is shown as

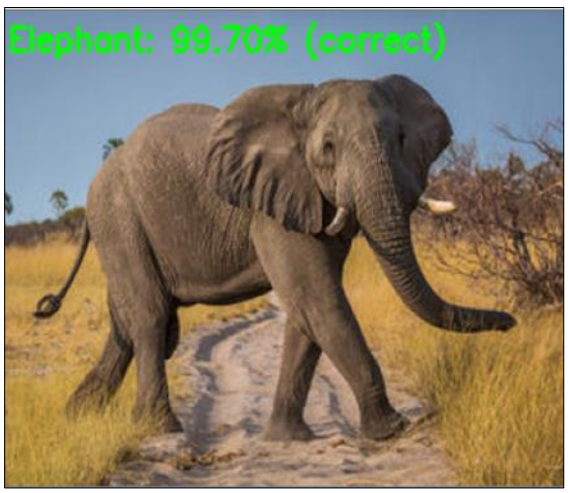

Figure 6 Result

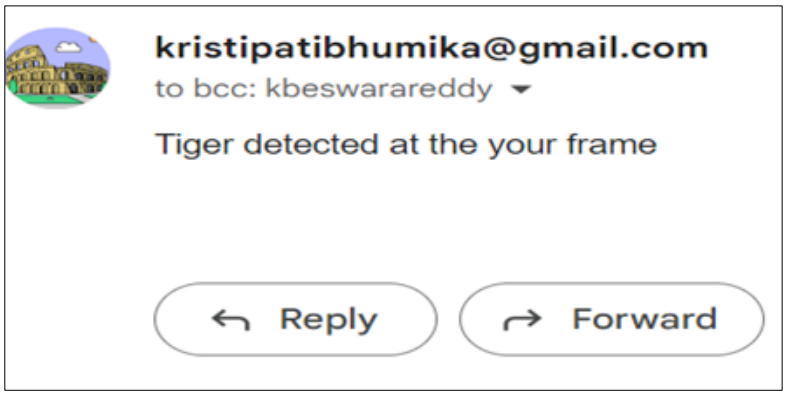

Figure 7 Email alert

The graphical representation of Training loss and accuracy with the parameters of loss/accuracy and epoch

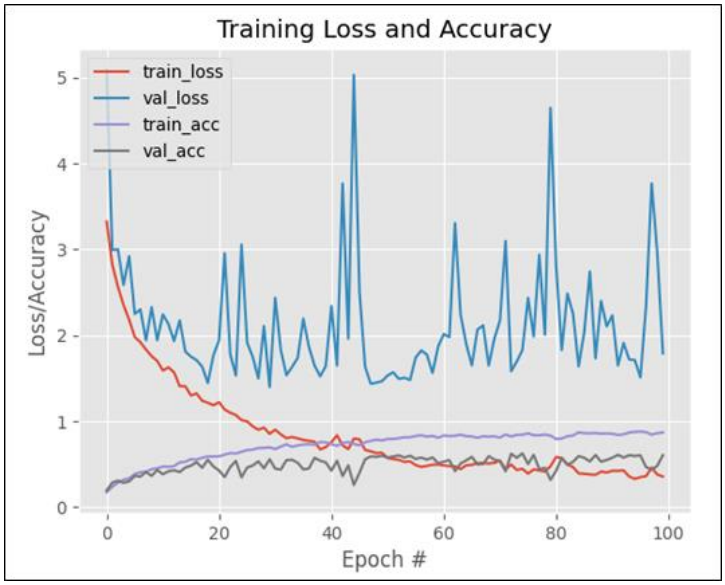

Figure 8 Graphical representation

5. Conclusion

The approach performed responds to animal intrusion on the farming fields. When the animal is detected upon intrusion, then an alert notification is sent to the farmer immediately. The animal captured is predicted through CNN. LBP and XGboost are used for the feature extraction of the image for the prediction. Through this crop damage can be reduced. The dataset is collected from Kaggle. The prediction obtained through this model is with better accuracy and satiable result.

Future work

In the future, ViT and lightGBM will be used to achieve faster and more accurate results. When compared to CNN, Visual Transformers (ViT) performs better in terms of computational efficiency and accuracy. And achieves better results.

Compliance with ethical standards

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Disclosure of conflict of interest

The author declares that there are no conflicts of interest or source of funding.

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