Safeguarding Agriculture: Using Deep Learning to prevent Animal Invasions

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ABSTARCT: The menace of crop damage due to animal attacks poses a significant threat to agricultural yields. With the expansion of cultivated land encroaching upon wildlife habitats, instances of crop raiding have escalated, exacerbating the human-wildlife conflict. Conventional mitigation measures employed by farmers have proven inadequate, and the impracticality of hiring guards to surveil crops deters a viable solution. Prioritizing Safeguarding crops from animal-induced destruction is imperative to ensure the safety of both humans and animals, while also prioritizing the welfare of the animals by diverting them harmlessly.

To address this challenge, a pioneering project is underway to develop an algorithm for wildlife detection. By leveraging image recognition technology, this algorithm aims to classify animals based on their visual profiles, enabling more efficient monitoring. The project entails installing cameras across the farm to surveil the surroundings continually throughout the day. By implementing this innovative approach, we endeavor to mitigate crop damage caused by animals while simultaneously promoting harmonious coexistence between humans and wildlife.

Keywords: Deep Learning, CNN, VGG-16, VGG-19.

I. Introduction

One of the major societal challenges affecting farming is the destruction of agricultural produce by wild animals. The disruption of wild animals by wild animals has always been a problem for ranchers. Deer, wild hogs, moles, elephants, monkeys, and other animals are a few that pose a threat to the harvest. The presence of these animals poses a significant threat as they can consume crops undetected by farmers, ultimately resulting in ruined harvests. Their ability to roam freely across fields without detection exacerbates the risk of crop damage, highlighting the urgent need for effective monitoring and mitigation measures. As a result, the yield may suffer a great loss, and additional financial security will be needed to deal with the damage**.** When utilising his invention, each farmer should be aware that animals are also present in the area and that they need to be protected from any possible suffering. An immediate solution should be found to this problem, along with a strong arrangement. As a result, our paper hopes find a solution to the central objective of the paper is to devise strategies aimed at preventing wild animals from encroaching upon agricultural fields in order to address this problem. Additionally, it emphasizes the importance of protecting these animals by employing non-lethal methods, such as scare tactics, to deter them from the fields, rather than resorting to lethal means. Additionally, the organisation seeks to safeguard people against animal assaults. To safeguard crops against animal assaults, we are employing an integrated approach in the various methods and algorithms have been developed in the field of deep learning to develop a monitoring and deterrent system. enhance safety measures against animal intrusion, involving IOT, sensing units, communicating devices for preliminary actions [8], diverting animals, and alerting farmers. Presented in this paper are reviews of animal detection methods using digital images. Sensor-based applications find utility in real-life scenarios across various fields. Utilizing such devices may reduce costs, ensure robustness, reliability, ease of access for farmers, and enable remote monitoring with lower energy consumption. The following methods are utilized to detect animal intrusion.

II. Literature Survey

This article assesses recent studies on animal infiltration detection and critiques their shortcomings. To mitigate agricultural losses, Salish et al. [6] propose techniques for detecting elephant encroachment. Their method involves using vibration sensors to trigger a camera trap, which captures images. Subsequently, an API analyzes these images to detect the presence of elephants, as suggested by Suganthi et al. Sailesh and co-authors employ a Raspberry Pi device with a camera to continuously capture images, searching for elephants among them. Depending on the identified animal, both systems can initiate various actions, such as emitting noises, flashing lights, or to deter further intrusion onto farms, aerosol solutions are sprayed.

Additionally, the article discusses a relevant intrusion detection system presented by Agadir et al. [1], which utilizes Convolutional Neural Networks (CNNs) for object recognition. The Animal Intrusion and Detection System (ANIDERS) [5] utilize a combination of AIR (Active Infrared) and PIR sensors to help farmers detect and prevent animal invasions, triggering alarms upon detection to discourage attackers. While the WWF-India3 pilot study reported a 68% accuracy rate in identifying animals within ANIDERS' range, significant room for improvement remains.

Critically, systems designed for detecting animal intrusions must ensure accurate species identification, considering that different animals react differently to stimuli. To minimize false positives, accurately identifying the animal and discerning its intentions before issuing notifications is crucial. Furthermore, uncertainties persist regarding the frequency of false warnings and whether the systems can confirm the success of deterring the animal once an alarm is triggered. It would also be beneficial to track the last known location and direction of travel for multiple animals in real-time. Addressing these challenges necessitates cost-effective solutions, such as employing small computing units like embedded systems. The article proposes resolving these issues through its suggested solution, offering an overview of its design in the subsequent section.

III. Proposed Work

By utilizing Convolutional Neural Networks (CNN) with the VGG16 model as a key component. Setting up a network of surveillance cameras strategically placed around the farm. These cameras will continuously capture images of the surrounding throughout the day. The system will be designed to send email notifications to farmers, alerting them to the presence of intruders in real-time, allowing for prompt response.

IV. Block Diagram

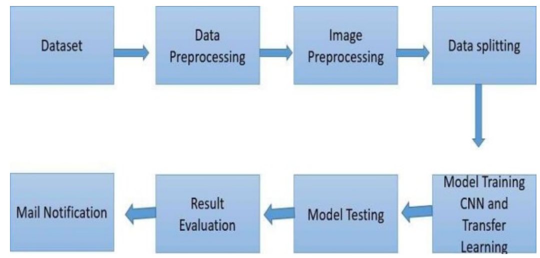

Fig 1: Block Diagram

1. Fetching Data :

Fetch, in the realm of computing, entails the retrieval of data through software, scripts, or hardware. Subsequently, once retrieved, this data can either be transferred to another location or presented on a screen for user interaction.

2. Data set:

A dataset comprises different and interconnected sets of data can be managed as a single unit and accessible individually or in combination. These datasets are structured in some form of data organization system.

3. Data Cleaning:

Data cleaning is the painstaking process of preparing data for analysis. This is achieved by removing or changing data that is unreliable, missing, unnecessary, repeated, or handled incorrectly structured. However, it goes beyond merely arranging rows or deleting information to accommodate new data. Data cleaning demands substantial effort. Its significance cannot be overstated, particularly in fostering a data-driven culture and ensuring precise forecasts.

It entails correcting grammatical and syntactic mistakes and standardizing data sets. Making corrections for errors like blank fields Finding redundant data points

4. Data preprocessing:

Many machine learning algorithms necessitate data to adhere to specific formatting guidelines, thus datasets typically require preparation before yielding valuable insights.

Some datasets contain missing, invalid, or challenging values for algorithms to process effectively. Missing or invalid data impedes algorithmic use, resulting in less accurate or misleading outcomes. While some datasets are relatively clean but require shaping, others lack essential business context, emphasizing the necessity for feature enrichment. Effective data preparation entails the creation of clean and meticulously curated data, ultimately leading to more practical and accurate model outcomes.

5. Model Training:

A dataset used to train an ML algorithm is called a training model. It consists of matching sets of input data that affect the output coupled with sample output data. By comparing the processed output with the sample output, this model is used to feed data into the algorithm. Through this iterative process known as "model fitting," adjustments are made to the model based on the correlation results. The accuracy of both the training dataset and the validation dataset plays a pivotal role in ensuring the precision of the model. Model training involves feeding data to an ML algorithm to aid in identifying patterns and making predictions**.**

V. System Implementation

A. Data pre-processing
B. Normalizing numeric data
C. Algorithms

A. Data Pre-Processing

Preparing raw data for analysis is known as data pre-processing, and it's a crucial first step in the creation of a machine learning model. In many cases, raw data is not clean or well-formatted, necessitating cleaning and formatting before any further operations can be performed. This process is crucial for ensuring that the data is in a usable state for training and testing machine learning algorithms.
Includes the following steps:
1. Obtaining the dataset
2. Importing libraries
3. Importing datasets
4. Finding Missing Data
5. Encoding Categorical Data
6. Splitting dataset into training and test set
7. Feature scaling

1. Getting the dataset
A dataset is a basic prerequisite for the creation of a machine learning model since these models depend solely on data to function. The dataset, which consists of collected data pertaining to a specific problem in a structured format, is crucial for training and testing machine learning algorithms. The benefits of user feedback for safe and effective medication usage are now being demonstrated. Consumer perceptions of their ailments and previously used medications are included in this data collection. Companies like 1mg may find this product useful line providing detailed ratings of the product's side effects on their website

2. Importing Libraries
Typically, the initial step involves importing the necessary libraries participating in the program. A library is a collection of modules that may be used and called from within an application.

3. Importing Datasets:
First, finding the CSV file's directory is necessary because many datasets are in CSV formats and then use the read.csv method in R-Studio to read it.

4. Finding Missing Data:
Following data pre-processing, the subsequent step involves addressing missing data within the datasets. The effectiveness of machine learning models can be significantly impacted by missing data. Implementing strategies for handling missing values present in the dataset is imperative.
One common approach to handling null values is by deleting the specific row or column containing them. However, this method is often considered inefficient as it may result in the loss of valuable information, ultimately affecting the accuracy of the output.

5. Encoding Categorical Data:
Whenever we have a text data need do apply text processing and clean it. In this text preprocessing first step punctuation symbols removal. First step want to remove some punctuation removal there isno using this symbol and get create some high

dimensionality. In the second step, we can remove stop words from the dataset using NLTK and then proceed with tokenization. Stop words are common words that often carry little meaning and can be removed to improve text analysis accuracy. In this step split the sentence into words and apply stemming. Stemming is nothing but convert the word into base form for example beautiful, beauty, be stain the base form is beauty. By using stemming concept we can reduce the dimensionally also. By doing the all the text preprocessing steps we will step preprocessed text. Apply text featurization concept on preprocessed.

6. Splitting the Dataset into Training set and Test Set

The division of our dataset into two separate sets a Training set and a Test set is the next critical step. The purpose of this division is to train our machine learning models on the Training set, then measure their predicted accuracy by assessing how well they perform on the Test set. It's essential to ensure that our model performs well not only on the Training set but also on unseen data, represented by the Test set. This practice helps prevent over fitting, when a model fails to generalize to new data despite doing remarkably well on the Training set. By striving for robust performance on both the Training, Test sets, we aim to develop machine learning models capable of accurately predicting outcomes across different datasets.

B. Normalizing Numeric data

In data preprocessing for machine learning purposes, normalization is a common technique utilized. Its objective is to adjust the values of numeric columns within a dataset to a standardized scale, while preserving the inherent differences in the ranges of values. This process becomes necessary when features exhibit disparate ranges, ensuring that each feature contributes equally during model training. In the context of machine learning, normalization involves translating data into a specified range, commonly [0,1], or alternatively, transforming data onto the unit sphere. Some machine learning algorithms benefit from normalization and standardization, particularly when Euclidean distance is used.

C. Deep Learning Algorithms

A. CNN

The development of artificial intelligence has been enormous in terms of bridging the capacities of both machines and people. To achieve incredible things, researchers and amateurs alike concentrate on numerous aspects of the field. One of these numerous domains is computer vision. The goal of this field is to enable machines to see and understand the world in a manner similar to humans. These machines will then be able to use this knowledge to perform natural language processing, media recreation, recommendation systems, image and video recognition, and image analysis and classification are just a few of the many jobs that fall within this broad category. Deep Learning has made significant strides in computer vision throughout time, mostly thanks to one particular algorithm called CNN. Send the data straight to the model after image processing and data splitting are finished; CNN architecture must first be defined. Initial import model sequentially, followed by an input layer that fixes the input shape images and provides the activation function. The input layer is then added, where 32 filters, a (5,5) kerner size, max pooling, and dropouts are added. This dropout aids in preventing over fitting in our model. Added two input layers with 64 and 128 filters, the same max pooling, a 5.5% kernel size, and dropouts using the Relu activation function once more.

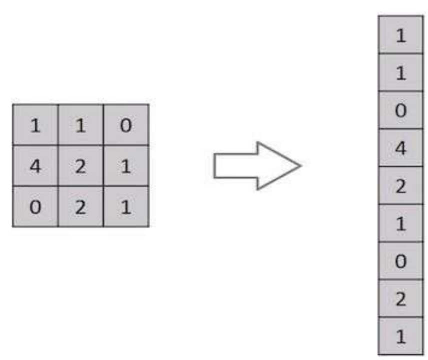

Fig2: Flattening of a 3x3 image matrix into a 9x1 vector

For extremely basic binary images, the method might be able to predict the class with an average precision score, but it would for intricate images with inter-pixel pixel relationships, performs poorly or not at all. The image measures five inches in height, five inches in width, and one number of channels (such as RGB). The green portion in the figure above corresponds to our 5x5x1 input image, I. The Kernel/Filter, represented by the letter K and shown in yellow, is the object in charge of executing the convolution process in the Convolutional layer's initial segment. We have decided on a 3x3x1 matrix for K.

Pooling layer

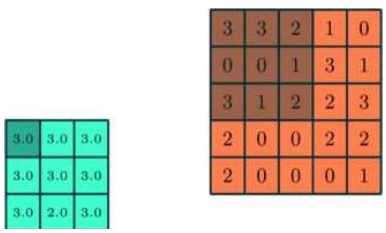

Fig3: Polling layer

Similar to the Convolutional Layer, the Pooling Layer is responsible for reducing the spatial extent of the Convolved Feature. This is intended to decrease the amount of computing power required to handle the data and minimize its dimensionality. Also helpful in obtaining dominating features that are positional and rotationally invariant, which keeps the model's training process going strong.

Max Pooling and Average Pooling are two different forms of pooling. Max pooling returns the maximum value from the area of the picture covered by the kernel, while Average Pooling yields the mean of all the values from the area of the picture covered by the kernel.

B.VGG16

In the field of image recognition, K. Simonyan and A. Zisserman's convolutional neural network, known as VGG16, is a seminal model. It sprang to prominence after achieving an astounding 92.7% top-5 test accuracy on the ImageNet dataset, which has over 14 million images spread across 1000 classifications, during the ILSVRC-2014 competition. What sets VGG16 apart is its architectural innovation: the replacement of larger kernel-sized filters in the initial layers with multiple consecutive 3x3 kernel-sized filters. This design choice allows for deeper network architectures without overly increasing the number of parameters, striking an optimal balance between model complexity and computational efficiency.

By leveraging this configuration, VGG16 excels at capturing intricate features and patterns within images, enabling robust and accurate classification. The cascading arrangement of smaller filters enhances the model's ability to extract meaningful features while maintaining a deep architecture. VGG16's success underscores the significance of architectural advancements in deep learning, paving the way for subsequent models and further advancements in computer vision research.

C. VGG19

Convolutional neural network VGG-19 was trained using a large dataset that included more than a million photos from the ImageNet database. This neural network building architecture boasts an impressive depth of 19 layers, making it proficient at classifying images into one of 1000 object categories. These categories span a diverse array of items ranging from everyday objects like keyboards, mice, and pencils to various animals. Through its rigorous training process, VGG-19 has acquired a nuanced understanding of features present in images across this broad spectrum.

When processing input images, VGG-19 expects a fixed size of 224x224 pixels with RGB channels, resulting in a matrix shape of (224,224,3). In essence, VGG-19 serves as a powerful tool for image classification tasks, leveraging its deep architecture to extract intricate features and make accurate predictions. The layers within the VGG-19 model are structured to progressively abstract and refine features from the input image, enabling it to discern intricate patterns and classify images with high accuracy.

A convolutional neural network called VGG-19 was trained using over the network consists of 19 layers, trained on a million photos from the ImageNet database is capable of categorizing pictures of 1000 different objects, including a keyboard, mouse, pencil, and numerous animals. Consequently, a vast array of image rich feature representations have

been trained by the network. The input to this network was an RGB fixed-size image measuring (224 * 224), which suggests that the matrix's structure was (224,224,3).
1. As a single preprocessing step, the mean RGB value of every pixel, computed over the whole training set, was subtracted..
2. They used kernels with a stride size of one pixel and a size of (3 * 3) to cover the full image. Spatial padding was used to preserve the image's spatial resolution.

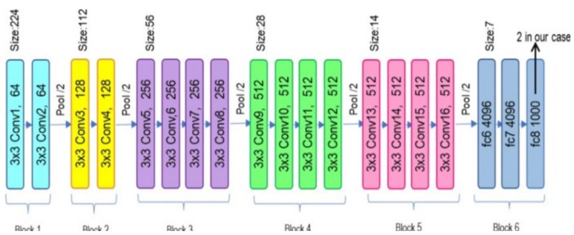

Fig4: VGG19 Architecture

VI. Results and Discussion

The suggested model will train the elephant, boar, and monkey picture collection by creating Convolutional Neural Network and transfer learning models. The saved model will be run on the driver code in order to compare the learned images with the new test images from the live capture. By means of speakers, an unpleasant noise is generated. If one of the trained animals is found during the live capture in order to scare it away. Different test photos areprovided, and their classes are recognised to verify the model's accuracy.

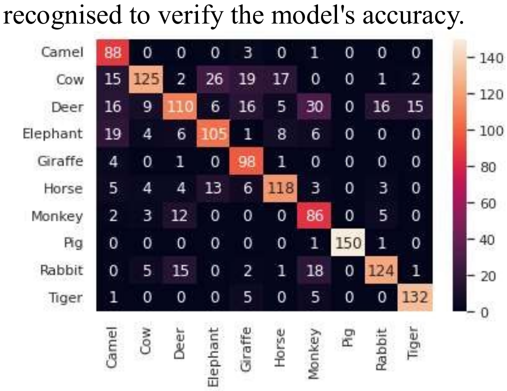

Fig5 : CNN MODEL CONFUSION METRIC PLOT

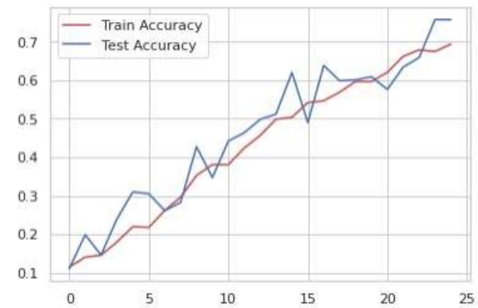

Fig 6: CNN MODEL TRAIN AND TEST ACCURACY PLOT PER EACH EPOCH

By using CNN got 75% accuracy we can check it from confusion metric also. Seeing this confusion matrix which class images are correctly classified and which class images Misclassified we can identify easily. Some camel images classified into cow, deer and elephant and some deer images classify into monkey and rabbit.
These all are the miss classified data points. We need to decrease these miss classified data points. So, we can see train and test data accuracy each class.

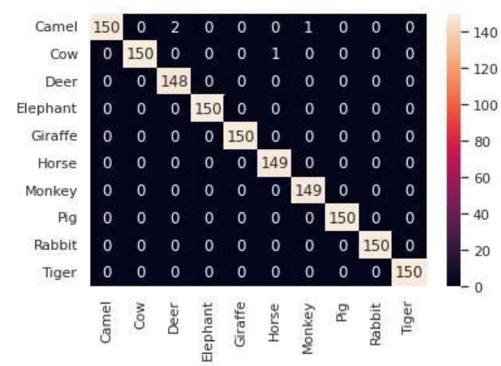

Fig 7:VGG-16 MODEl CONFUSION METRIC PLOT

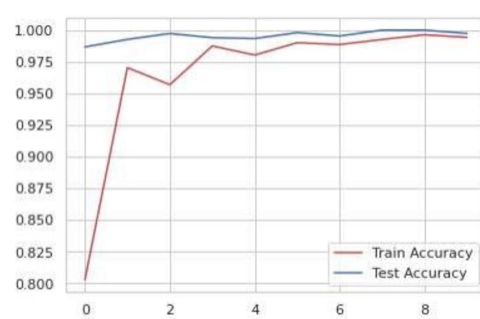

Fig8 : VGG-16 MODEL TRAIN AND TEST ACCURACY PLOT PER EACH EPOCH

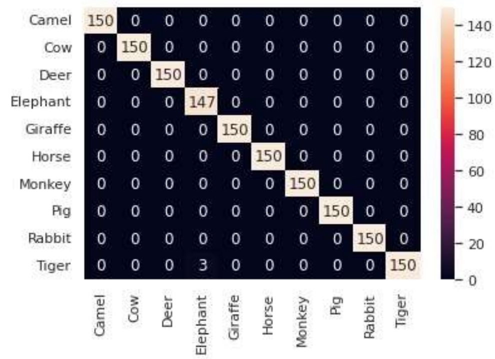

Fig 9: VGG-19 MODEL CONFUSION METRIC PLOT

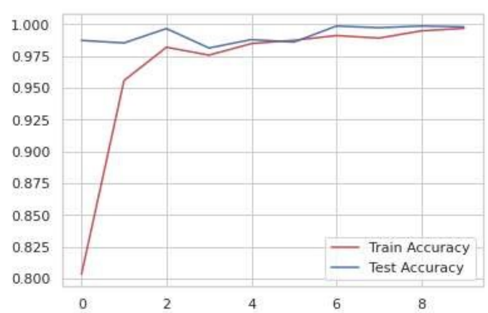

Fig 10: VGG-19 MODEL TRAIN AND TEST ACCURACY PLOT PER EACH EPOCH

VII. CONCLUSION

The problem of wild animals eating crops has become a major social issue in modern times. Put differently, every farmer should utilize the crop productivity that he or she should be conscious of and mindful of the reality that animals are sentient beings who require protection from potential harm. It needs to be addressed immediately and effectively. As a result, this initiative has a great deal of social significance because it will free farmers from the needless labor associated with field protection, help them protect their fields, and shield them from significant financial losses.

VIII. REFERENCE

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