IOT AND MACHINE LEARNING-BASED EFFECTIVE MONITORING SYSTEM FOR CROPS AGAINST ANIMAL INTRUSION

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Abstract
Apart from all the other vocations, the agricultural sector accounts for 20% of the Indian GDP. However, agricultural yield and profitability are currently the main issues. It's because animals got involved. These animal attacks are costing farmer's money in their agricultural endeavors. To overcome this issue, the suggested approach offers IOT and machine learning algorithms. The Raspberry Pi uses machine learning methods like CNN (convolution neural network), VGG16, and SSD to recognize animals and find objects in images additionally, the function of IoT via Thing Speak, which is helpful for real-time visualization and analysis of photos via cloud.
Keywords: IoT, Raspberry pi, Machine learning, RCNN, Keras, VGG16, Mobile Net

Introduction

Due More than 60% of the population in India is directly or indirectly dependent on agriculture. Given that agriculture forms the backbone of Indian conservation. Where they need to get the food to feed this enormous population that is expanding year by year while the amount of land available for agriculture shrinks. Regarding food commodities, it is anticipated that they would rise by roughly 15-20% in the next five years [1]. However, due to differences between or within farms, such as environmental circumstances, a significant portion of the population is dependent on this industry. But nowadays, animal infiltration is the principal cause of these agricultural problems. Farmers might encounter animal conflict in hilly places near woods, where loss occurs most frequently. Ancient days the animal attacks were stopped by some traditional methods such shot gun, string and stone. Later, a few attempts were done using technology with IoT and Machine learning algorithms. In our proposed model we are using IoT and Machine learning techniques to solve this issue.

The Internet of Things (IoT) manages the linked objects and sends data through the network. Using sensors and various electrical components, IoT automation permits the combination of present data from the cropland [2]. We have the collaboration with pi camera interfacing with cloud which a newdomain. The pi camera uses to capture the images day and night. The inexpensive and simple-to-use Raspberry Pi serves as a controller for physical components and data conveyed, which employs the TC/IP code [3].

Machine learning is a bunch of expert system utilized for analyses of data. It is used into detect the objects and patterns to make a decision. The algorithms used to classify the objects and their tested. Its purpose is to send important information to the framers, which are under the supervision of the Raspberry Pi controller. I'm motivated by all of this to offer a strong model to defend agricultural damage caused by animal invasion due to modern technologies.

Proposed Method

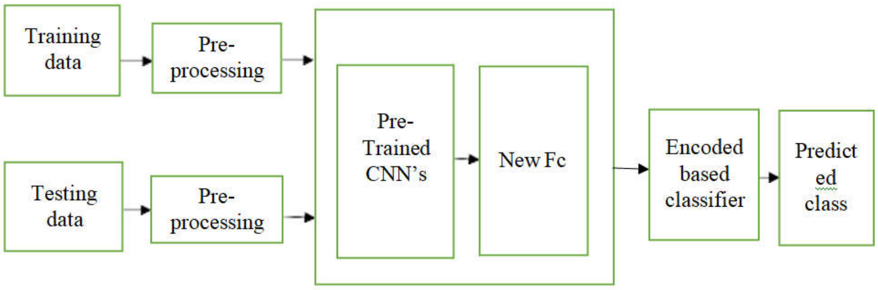

Figure 1: Learning Stage and Experimental Stage of Suggested pattern

In Figure 1, the Learning and experimental stages of the VGG19 pattern are shown. The pattern is first laden through post-processing pictures and tags from the Kaggle database, and after the database is divided among drilling, authenticating, and evaluating databases. The drilling and authentication bases are stuffed through accession to suitable into the assumed VGG19 during the learning stage. The structure of the assumed architecture is evaluated with enhanced learning data and authenticated with authentication data at each era. Using learning parameters including the number of eras, small batch size, regularisation, studying rate, and other factors, the drilling is carried out. The evaluating stage involves putting the experienced model to the test on a evaluating database andauthenticating it with measure performance.

Database:

A machine learning model needs a lot of information to be trained. Such datasets containing asignificant amount of labelled data are uncommon in the field of crop imaging.

The dataset for this study was compiled from the images of animals in the Kaggle repository.

Fig 2: Sample dataset from Animals Images

The folders are separated into three categories: training, validation, and testing. To prevent overfitting, 80 percent of the photos are utilized as training data, 10 percent are used as validation, and the final 10 percent are used for testing.

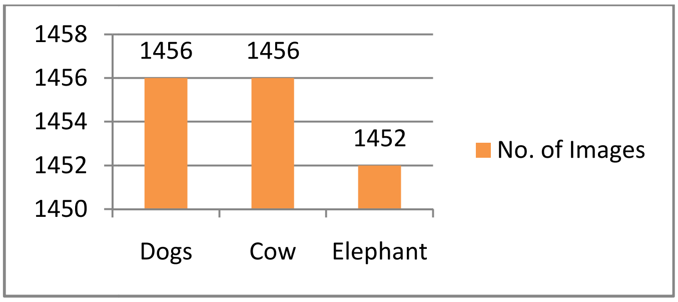

Table 1: Details of Collected Dataset

CNN Architecture:

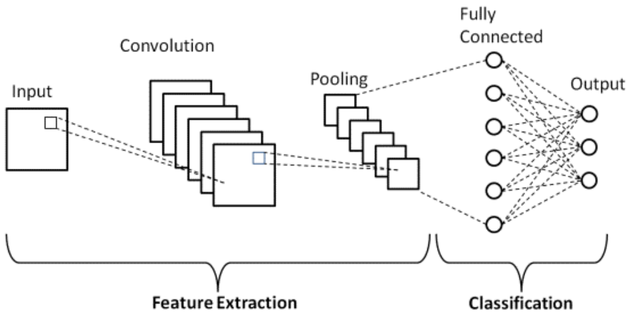

Fig 3: CNN Architecture

Figure 3 shows the CNN design as well as the steps involved in creating each component. A convolutional network's starting layer is the convolutional matrix. The affine layer is the final layer, even though convolutional layers, further convolutional maps, or merging layers, can come after it. The CNN becomes more complicated with each layer, identifying big areas of the picture. primary layers emphasize common components like shades and edges.

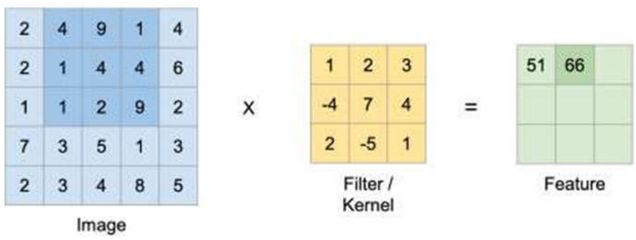

Fig 4: Convolution Matrix

The essential element of a CNN is the convolution layer, which is also where the possibility of estimation takes place. It needs input information, a filter, and a feature map around other elements. Consider that the input will be a color picture that is collected of a 3D element matrix. It follows that the input will have three boundaries —a height, a width, and a depth—that match the RGB color scheme in a picture. Further, we have a characteristic detector, also referred to as a kernel or a filter, which will copy the pictures various fields to see if the feature is present. Convolution illustrates thismethod. (1)

Pooling layer

Down bounding, also known as pooling layers, diminishes the number of constraints in the input and does linearity devaluation. Similar to the convolution matrix, the merging procedure sweeps a filter over the unified input, but this filter weightlessness. Rather, the kernel utilizes an accumulation function to fill the output array with characters from the fortunate field. In general, there are two categories of merging:

Max merging: The filter chooses the input element with the highest value move to the output range as it advances across the input. As a side note, this process is implemented most regularly than average merging.

Average merging: The average value inside the fortunate field is resolved as the filter advances across the input, and it is after sent into the output range.

Affine layer:

This layer conducts the classification operation using the features that were isolated utilizing the different filters and previous layers. While convolutional and merging layers generally use ReLu tasks to classify inputs, FC loops normally utilize a SoftMax activation task to do so, producing a feasibility ranging from 0 to 1.

Results and Discussions:

Validation measures are employed to assess the performance of various machine learning networks. The following validation indicators were taken into account while assessing how well the proposed VGG19 model performed. The work measures based on TP, FP, TN, and FN are as follows.

$$\text{Accuracy} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (4)$$

$$\text{Sensitivity} = \frac{T_P}{T_P + F_N} \quad (5)$$

$$\text{Precision} = \frac{T_P}{T_P + F_P} \quad (6)$$

$$\text{F1-Score} = 2\frac{PPV * TPR}{PPV + TPR} \quad (7)$$

Fig 5 displays the overall performance classification for Animals in terms of Accuracy, Sensitivity, Precision, and F1-Score. In comparison to previous Machine learning networks as Alex-Net, VGG-16, VGG-19, MobileNetV2, covEnNet our proposed technique demonstrated the greatest results. Fig.7,8 displays a Training and validation graphs of accuracy and loss of VGG19.

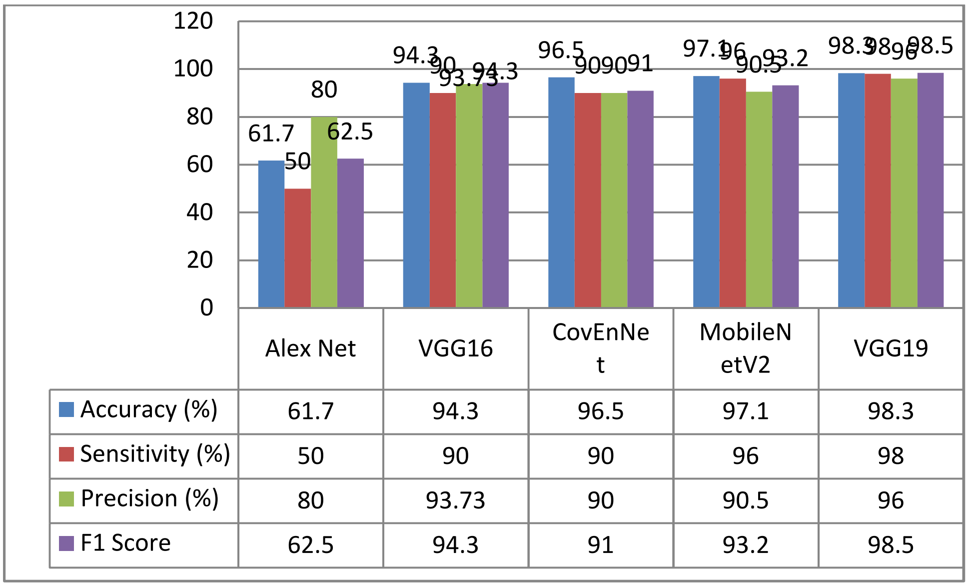

Fig 5 : Performance metrics of different machine learning networks in terms of Accuracy, Sensitivity, Precision and F1 Score.

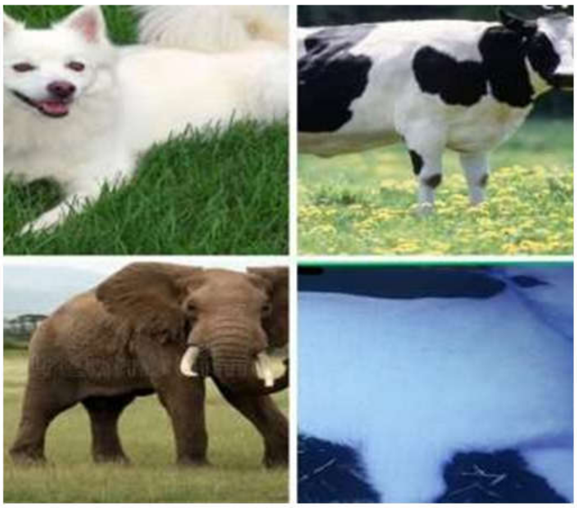

Fig 6: Input Image

Fig 7: Output Image

Fig 8: Learning and verification Accuracy graph of VGG19

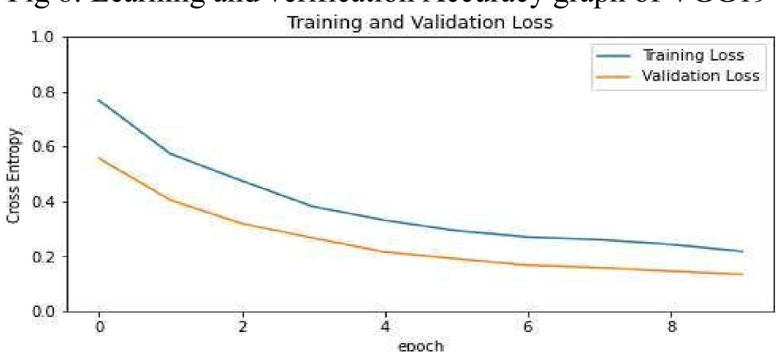

Fig 9: Learning and verification loss graph of VGG19

Conclusion

The use of IoT and machine learning technologies is used to safeguard crops against animal encroachment in order to successfully cultivate and profit from the crops. In order to categories animals using photos of animals, four different previously published logical CNN-based machine learning algorithms were trained and tested. Numerous approach models, including VGG19, VGG16, Alex-Net, covEnNet, and MobileNetV2, were included in our suggested model. In comparison to previous machine learning networks, our suggested model, called VGG19, performs better and is best suited for animal detection since it achieves a higher accuracy of 98.3 percent.

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