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ijircce@gmail.com



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Using Machine Learning, A Camera Vision-based Animal Beat Back System for Agriculture

Mr.R.Karthik, M.E , Sahana Parveen. M, Sabari.P, Praimathi.K, Priyadharshini.N.K

Assistant Professor, Department of CSE, Saranathan College of Engineering, Trichy, India

UG Student, Department of CSE, Saranathan College of Engineering, Trichy, India

ABSTRACT: As a result of human interference with natural habitats and deforestation, crop raiding by animals has emerged as one of the most prevalent human-animal conflicts. Wild animals can assault farmers working in the fields and seriously harm agricultural harvests. Due to agricultural raiding by wild animals like elephants, wild boar, and deer, farmers experience significant crop loss. The protection of crops against assaults by wild animals is one of the primary concerns of today's farmers. There are numerous conventional methods for dealing with this issue, both fatal (such as shooting or trapping) and non-lethal (such as scarecrows, chemical or organic repellents, mesh, or electric fences). Farmers have attempted a variety of methods to stop animal raids, such as lighting firecrackers to keep an eye on the pitch throughout the night, but none of them have been successful. However, some of the conventional techniques cause environmental pollution that affects both people and ungulates, while others are expensive, require a lot of maintenance, and have a limited effectiveness and reliability. In this project, we create a system that combines animal detection and identification using computer vision using DCNN with particular ultrasonic emission (i.e., different for each species) that serves as a deterrent. The edge computing device turns on the camera, then uses its DCNN software to identify the target. If an animal is discovered, it then sends a message to the Animal Repelling Module with information about the type of ultrasound that should be created based on the animal's category.

KEYWORDS: Animal Detection, Deep Learning, DCNN, Repellent, Artificial Intelligence, and Animal Recognition.

I.INTRODUCTION

A few of the revolutions in agriculture include the domestication of animals and plants a few thousand years ago, the systematic use of crop rotations and other improvements in farming techniques a few hundred years later, or the "green revolution" with systematic breeding and the widespread use of man-made fertilizers and pesticides a few decades later. The exponential growth in information and communication technology (ICT) use in agriculture has sparked the fourth industrial revolution in agriculture. For usage in agriculture, autonomous robots have been developed that can do tasks including mechanical weeding, fertilizer application, and fruit harvesting. The development of unmanned upstanding vehicles with independent flight control, as well as feather-light and important hyperspectral shot cameras able of calculating crop biomass development and fertilization status, pave the way for sophisticated ranch operation advice. likewise, decision- tree models that use optic information to separate between factory conditions are now available. Grounded on distant seeing signals and detectors or selectors linked to the beast, virtual hedge technologies enable cow herd operation. Smart husbandry is a operation conception that focuses on furnishing the agrarian business with the structure to harness sophisticated technology, similar as big data, the pall, and the internet of effects(IOT), to track, cover, automate, and assay conditioning. Also known as perfection husbandry, smart husbandry is software- managed and detector- covered. Smart husbandry is growing in significance due to the combination of the expanding global population, the adding demand for advanced crop yield, the need to use natural coffers efficiently, the rising use and complication of information and communication technology and the adding need for climate-smart husbandry.

II.EXISTING SYSTEM

Wild Creatures are a special challenge for growers throughout the world. creatures similar as deer, wild boars, rabbits, intelligencers, mammoths, monkeys, and numerous others may beget serious damage to crops. They can damage the shops by feeding on factory corridor or simply by running over the field and stamping over the crops. thus, wild creatures may fluently beget significant yield losses and provoke fresh fiscal problems. Another thing to think about is

the need for very cautious approach to wild beast crop protection. In other words, while exercising his crop product, every planter should be apprehensive and take into consideration the fact that creatures are living beings and need to be defended from any implicit suffering.

A. Farmers Traditional Approach

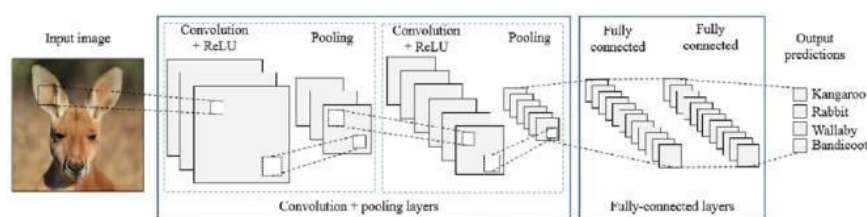
There are different being approaches to address this problem which can be murderous(e.g., firing, trapping) and non-lethal(e.g., scarecrow, chemical repellents, organic substances, mesh, or electric walls), firecrackers, bright lights, fire, beating cans, and tykes . Non-chemical control of fund gophers. 22 hem fire rifle or a shotgun can be used to dispatch woodchucks. Some stir- actuated water sprayers have been developed that spot catcalls when they break the stir-detecting. Growers use Agrarian walls like line walls, plastic walls, electric walls, etc., as one of system to cover their ranch lands. they also use some natural repellents, chemical repellents and also biophysical barriers.

III.PROPOSED SYSTEM

AI Computer Vision grounded DCNN for detecting beast species, and specific ultrasound emigration(i.e., different for each species) for repelling them. design, deployment and assessment of an intelligent smart husbandry repelling and covering IOT system grounded on bedded edge AI, to descry and fete the different kinds of beast, as well as induce ultrasonic signals acclimatized to each species of the animal. This combined technology used can help growers and agriculturists in their decision making and operation process.Deep literacy in the form of Convolutional Neural Networks(CNNs) to perform the beast recognition.

A.DCNN

CNNs are a order of Neural Networks that have proven veritably effective in areas similar as image recognition and bracket. CNNs are a type of feed-forward neural networks made up of numerous layers. CNNs correspond of pollutants or kernels or neurons that have learnable weights or parameters and impulses. Each sludge takes some inputs, performs complication and voluntarily follows it with anon- linearity. A typical CNN armature can be seen as shown inFig.3.1. The structure of CNN contains Convolutional, pooling, remedied Linear Unit (ReLU), and Completely Connected layers.



a)Convolutional Layer: Convolutional layer, first the fundamental building unit of a convolutional network, which does the majority of the computational effort, is the convolutional estate. Convolutional estate's main goal is to extract features from the input data, which is a picture. By learning picture attributes from the small regions of the input image, convolution preserves the spatial relationship between pixels. By using a group of teachable neurons, the input image is distorted. The result is a point chart, also known as an activation chart, which is then provided as input data to the ensuing convolutional estate.

b)Pooling Layer: Pooling estate reduces the dimensionality of each activation chart but continues to have the most important information. The input images are divided into a set of non- lapping blocks. Each region is down- tried by anon-direct operation similar as average or maximum. This estate achieves better generality, hastily confluence, robust to translation and deformation and is generally placed between convolutional layers.

c)ReLU Layer: ReLU is a non-linear operation and includes units employing the rectifier. Since it is applied per pixel and is an element-wise operation, it replaces all negative values in the feature map with zero. In order to comprehend how the ReLU functions, we first suppose that the neuron input is given as x ,and that the rectifier is defined in the literature for neural networks as $f(x)= \max (0, x)$.

d)Fully Connected Layer: Every sludge in the previous subcaste is connected to every sludge in the following subcaste, which is what is meant by the term "Completely Connected Subcaste" (FCL). Convolutional, pooling, and ReLU layers provide images of the input image's prominent characteristics. Using the FCL involves using these attributes to divide the input image into brightly coloured groups based on the training dataset. FCL is viewed as the final pooling subcaste providing the features to the SoftMax activation function of the classifier. There are a total of 1 chances per Completely Connected Subcaste member for an affair. Utilizing Softmax as the activation function ensures this. The SoftMax function takes an arbitrary vector of real- valued scores and squashes it to a vector of values between 0 and 1 that add to one.

B.Generation of Repelling Ultrasound

Animals often have a far greater sound sensitivity threshold than humans. They can hear noises with lower frequencies than the human ear. For example, although humans have an audible range of 64Hz to 23KHz, goats, sheep, domestic pigs, dogs, and cats have ranges of 78Hz to 37KHz, 10Hz to 30KHz, 42Hz to 40.5KHz, 67Hz to 45KHz, and 45Hz to 64KHz. Animals are agitated when ultrasounds are produced near the crucial detectable range, causing them to flee away from the sound source. At the same time, even when the frequency range is beyond the human ear, these ultrasounds do not cause difficulties. Human eardrums have a far lower specific resonance frequency than animal eardrums and cannot vibrate at ultrasound frequencies. Furthermore, such a solution is non-lethal and has no effect on environmental pollution or the landscape.

C.Notification System

The detecting system kept track of each detection's date and time. All animal movements inside the enclosure were also recorded by cameras and a video recording system. To assess the system's dependability, the detection log was contrasted with the images from the cameras, which also contained a date and time stamp. To the registered mobile number is delivered a message alert.

IV. HARDWARE SPECIFICATIONS

Processors: Intel® Core™ i5 processor 4300M at 2.60 GHz or 2.59 GHz (1 socket, 2 cores, 2 threads per core), 8 GB of RAM
Disk space: 320 GB
Operating systems: Windows® 10, macOS*, and Linux

V. SOFTWARE DESCRIPTION

Server Side : Python 3.7.4 (64 bit) or (32 bit)
Client side : HTML,CSS,BOOTSTRAP
IDE : Flask1.1.1
Back end : MySQL 5
Server : Wampserver 2i

VI.WORKING PRINCIPLE

A.Animal Repellent Web Dashboard

This system works in real time to detect the animals in the fields. The system enables the farmer to have a real time view of his fields from any place via internet and even provides manual buzzer controls if the need arises to use them. Thus, the farmer is in effective control of the system and can manually sound the buzzer if needed. This system is economical as compared to many of the existing solutions like electric fences, brick walls and manual supervision of the fields. This system is very effective in driving off the animals from the fields and keeping them away. It accurately determines the presence of animals in the fields and sounds the buzzer. It does not sound the buzzer due to the presence of a human being or due to some random motion. The ultrasonic buzzer is very effective against animals and causes no noise

pollution. This system is totally harmless and doesn't injure animals in any way. It also doesn't cause any harm to humans. Also, this system has a very low power requirement thus reducing the hazards of electric shocks.

B. Animal Recognition

a) Training Phase

This module begins by reflection of beast dataset. These templates also come the reference for assessing and registering the templates for the other acts tipping up/ down, moving closer/ farther, and turning left wing/ right.

b) Animal Image Acquisition

Beast- 10N dataset contains 5 dyads of confusing creatures with a aggregate of 55,000 images. The 5 dyads are as following(cat, lynx),(jaguar, cheetah),(wolf, runner),(chimpanzee, orangutan),(hamster, guinea gormandizer). The images are crawled from several online hunt machines including Bing and Google using the predefined markers as the hunt keyword.

c) Pre-processing

Beast Image pre-processing are the way taken to format images before they're used by model training and conclusion. The way to be taken are

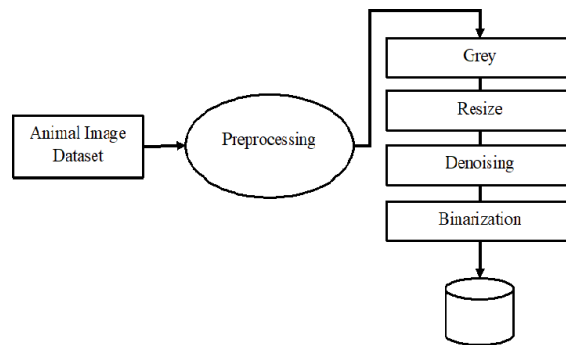
- Read image
- RGB to Grey Scale conversion
- Resize image

Original size(360, 480, 3) —(range, height, no. RGB channels)

Resized(220, 220, 3)

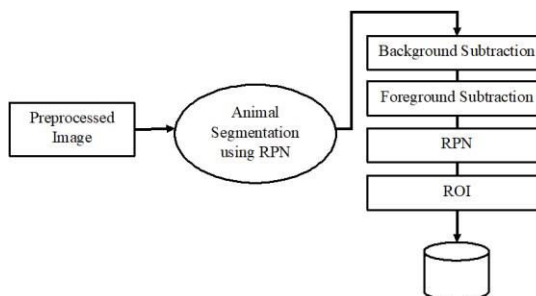
Remove noise(Denoise)

smooth our image to remove unwanted noise. We do this using gaussian blur.



Binarization

Image binarization is the process of taking a grayscale image and converting it to black- and-white, basically reducing the information contained within the image from 256 tones of slate to 2 black and white, a double image.

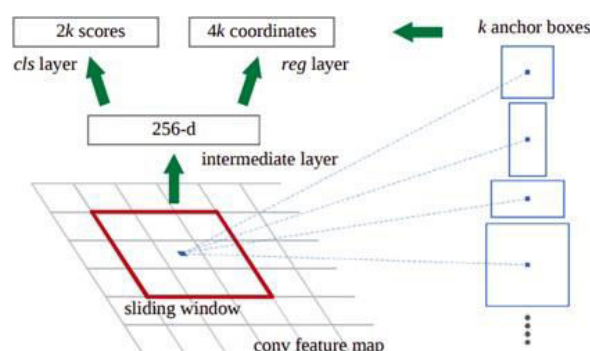


Beast discovery and segmentation system grounded on bettered RPN. RPN is used to induce RoIs, and RoI Align faithfully preserves the exact spatial locales. These are responsible for furnishing a predefined set of bounding boxes of different sizes and rates that are going to be used for reference when first prognosticating object locales for the RPN.

RG is a simple image segmentation system grounded on the seeds of region. It's also classified as a pixel- grounded image segmentation system since it involves the selection of original seed points. This approach to segmentation examines the neighbouring pixels of original “ seed points ” and determines whether the pixel neighbours should be added to the region or not grounded on certain conditions. In a normal region growing fashion, the neighbour pixels are examined by using only the “ intensity ” constraint. A threshold position for intensity value is set and those neighbour pixels that satisfy this threshold is named for the region growing.

d)RPN

A Region Offer Network, or RPN, is a completely convolutional network that contemporaneously predicts object bounds and objectless scores at each position. The RPN is trained end- to- end to induce high- quality region proffers. It works on the point chart(affair of CNN), and each point(point) of this chart is called Anchor Point. For each anchor point, we place 9 anchor boxes(the combinations of different sizes and rates) over the image. These anchor boxes are cantered at the point in the image which is corresponding to the anchor point of the point chart.



e)Training of RPN.

To know that for each position of the point chart we've 9 anchor boxes, so the total number is veritably big, but not all of them are relevant. However, and if the anchor box doesn't have an object within it also we can relate it as background, If an anchor box having an object or part of the object within it also can relate it as a focus.

So, for training, assign a marker to each anchor box, grounded on its crossroad over Union(IoU) with given ground verity. We principally assign either of the three(1,-1, 0) markers to each anchor box.

- Marker = 1(Focus) An anchor can have marker 1 in following conditions,
- If the anchor has the loftiest IoU with ground verity.
- If the IoU with ground verity is lesser than0.7.(IoU>0.7).
- Marker = -1(Background) An anchor is assigned with-1 if IoU<0.3.
- Marker = 0 If it doesn't fall under either of the below conditions, these types of anchors don't contribute to the training, they're ignored.

After assigning the markers, it creates the mini-batch of 256 aimlessly picked anchor boxes, all of these anchor boxes are picked from the same image.

The rate of the number of positive and negative anchor boxes should be 11 in the mini-batch, but if there are lower than 128 positive anchor boxes also we pad the mini-batch with negative anchor boxes.Now the RPN can be trained end- to- end by backpropagation and stochastic grade descent(SGD).

The processing way are

- Handpick the original seed point
- Method the neighbouring pixels intensity threshold
- Check threshold of the neighbouring pixel
- Thresholds satisfy- named for growing the region.
- Process is repeated to end of all regions.

f)Animal Detection

Therefore, in this module, Region Offer Network(RPN) generates RoIs by sliding windows on the point map through anchors with different scales and different aspect rates. Beast discovery and segmentation system predicated on bettered RPN. RPN is used to induce RoIs, and RoI Align faithfully preserves the exact spatial locales. These are responsible for furnishing a predefined set of bounding boxes of different sizes and rates that are going to be used for reference when first predicting object locales for the RPN.

g)Feature Extraction

In point birth process, the useful information or characteristics of the image are pulled in the form of statistical, shape, colour and texture features. The Transformation of the input image into features is called point birth. Features are pulled by using point birth ways. Features are pulled predicated on texture, boundary, spatial, edge, transfigure, colour and shape features. Shape- predicated features are divided into the boundary and region- predicated features. Boundary features are also called figure- predicated which uses boundary corridor. Boundary predicated features are geometrical descriptors(fringe, major axis, minor axis, border, curiosity and wind), Fourier descriptors and statistical descriptors(mean, disunion, standard divagation, dispose, energy and entropy). Region predicated features are texture features as GLCM.

h)Gray Level Co- circumstance Matrix

GLCM is a alternate- order statistical texture analysis system. It examines the spatial relationship among pixels and defines how constantly a combination of pixels are present in an image in a given direction Θ and distance d . Each image is quantized into 16 gray situations(0 – 15) and 4 GLCMs(M) each for $\Theta = 0, 45, 90,$ and 135 degrees with $d = 1$ are attained. Five characteristics (Eq. 13.30 – 13.34) are extracted from each GLCM. thus, there are 20 features for each image. Each point is formalized to range between 0 to 1 before passing to the classifiers, and each classifier receives the same set of features. The second category is shape features, which include volume, surface area, surface area to volume ratio, maximum 3D diameter, maximum 2D diameter for axial, coronal and sagittal plane respectively, major axis length, minor axis length and least axis length, sphericity, elongation, and other features. These features characterize the shape of the tumour region. The third category is texture features, which include 22 Gray level co-occurrence matrix (GLCM) features, 16 Gray level run length matrix (GLRLM) features, 16 Gray level size zone matrix (GLSZM) features, five neighbouring Gray tone difference matrix (NGTDM) features and 14 Gray level dependence matrix (GLDM) Features. These features characterize the texture of the tumour region. Animal images during the classification process. This will ensure proper training and therefore the best possible performance.

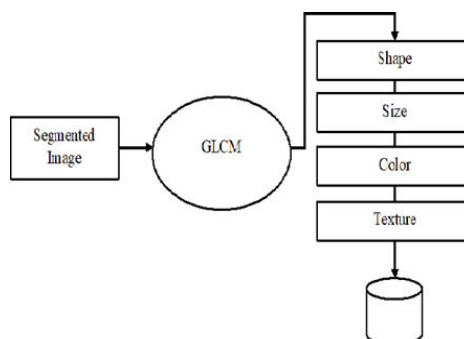
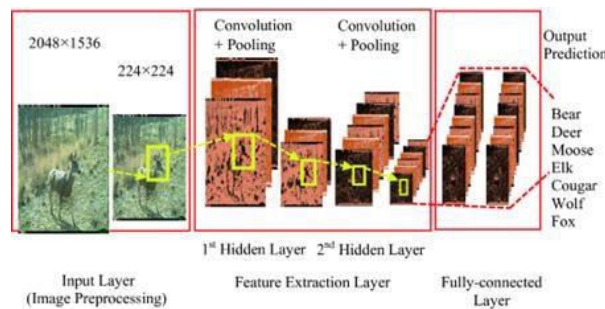


TABLE I .Formulas to calculate Texture Features from GLCM

Sl.No	GLCMFeature	Formula
1.	Contrast	$\sum_{i,j=0}^{N-1} P_{ij} (i-j)^2$
2.	Correlation	$\sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu_i)(j-\mu_j)}{\sigma_i \sigma_j}$
3.	Dissimilarity	$\sum_{i,j=0}^{N-1} P_{ij} i-j $
4.	Energy	$\sum_{i,j=0}^{N-1} P_{ij}^2$
5.	Entropy	$-\sum_{i,j=0}^{N-1} P_{ij} \ln P_{ij}$
6.	Homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2}$
7.	Mean	$\mu_i = \sum_{j=0}^{N-1} i(P_{ij}), \mu_j = \sum_{i=0}^{N-1} j(P_{ij})$
8.	Variance	$\sigma_i^2 = \sum_{j=0}^{N-1} P_{ij} (i-\mu_i)^2, \sigma_j^2 = \sum_{i=0}^{N-1} P_{ij} (j-\mu_j)^2$
9.	StandardDeviation	$\sigma_i = \sqrt{\sigma_i^2}, \sigma_j = \sqrt{\sigma_j^2}$



The CNN creates point charts by casting up the convolved grid of a vector- valued input to the kernel with a bank of pollutants to a given subcaste. also anon- linear remedied direct unit(ReLU) is used for calculating the activations of the convolved point charts. The new point chart attained from the ReLU is regularized using original response normalization(LRN). The affair from the normalization is farther reckoned with the use of a spatial pooling strategy(outside or average pooling). also, the use of powerhouse regularization scheme is used to initialize some unused weights to zero and this exertion most frequently takes place within the completely connected layers before the bracket subcaste. Eventually, the use of softmax activation function is used for classifying image markers within the completely connected subcaste.

B.Animal Identification

After landing the beast image from the ranch Camera, the image is given to beast discovery module. This module detects the image regions which are likely to be mortal. After the beast discovery using Region Offer Network(RPN), beast image is given as input to the point birth module to find the crucial features that will be used for bracket. The module composes a veritably short point vector that's well enough to represent the beast image.

C.Prediction

In this module the matching process is done with trained classified result and test beast image with beast dataset classified train. Hamming Distance is used to calculate the difference according to the result the vaticination delicacy will be displayed. Then, it's done with DCNN with the help of a pattern classifier, the uprooted features of beast image are compared with the bones stored in the beast database. The beast image is also classified as beast type.

D.Repellent

Monitoring window detecting the presence of creatures also it enables repeller module to repelling them through the generation of ultrasounds, which has lately been proven as an volition, effective system for guarding crops against

prognosticated creatures. creatures generally have a sound sensitive threshold that's far advanced than humans. They can hear sounds having lower frequentness with respect to the mortal observance. For case, while the audible range for humans is from 64Hz- 23KHz, the matching range of scapegoats, lamb, domestic gormandizers, tykes and pussycats is 78Hz- 37KHz, 10Hz- 30KHz, 42Hz-40.5 KHz 67Hz- 45KHz and 45Hz-64KHz independently.

E.Monitoring and Visualizing

The system works in real time descry the brutes in the field, in addition the farmers can pierce the view of their fields ever. Type of beast and also the count can be given. The beast recognition module will partake the data over the pall regularly through a Wi- Fi connection. The pall setup will correspond of a private pall case running on a machine. The data shared will be used to assay the patterns and responses of wild brutes. The farmer can visualize the crimes if any, resolve them, and achieve better results. The proportion of positive cases that are labelled as similar is known as the TP. FP is the proportion of negative cases that are labelled as positive. FN is the number of positive cases classified as negative, and TN is the number of negative cases classified as positive.

a)Notification

The dispatch and SMS advertisement conforming of captured image is notified to the user regarding the detected stir in this phase. The dispatch is transferred to registered dispatch id and SMS is transferred to the Telegram account of the user to the registered number.

b)Performance Analysis

In this module we suitable to find the performance of our system using perceptivity, particularity AND delicacy of Data in the datasets are divided into two classes not beast(the negative class) and beast and type(the positive class). perceptivity, particularity, and delicacy are calculated using the True positive(TP), true negative(TN), false negative(FN), and false positive(FP).The proportion of positive cases that are labelled as such is known as the TP. FP is the proportion of negative cases that are labelled as positive. FN is the number of positive cases classified as negative, and TN is the number of negative cases classified as positive. The important points involved with the performance criteria are mooted predicated on the terrain of this design.

True Positive(TP) : There's a Beast and the algorithms descry carnal name.

False Positive(FP): There's no Beast, but the algorithms descry as Beast and display Beast name.

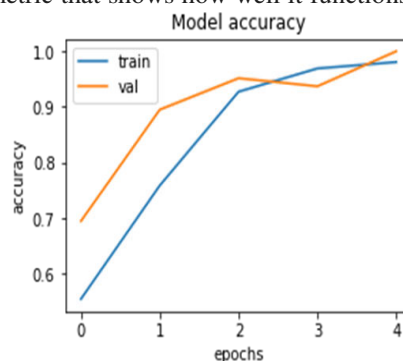
False Negative(FN): There's a Beast, but the algorithms don't descry Beast and name.

True Negative(TN) : There's no Beast, and nothing is being detected.

	True (relevant)	False (not relevant)
Positive (retrieved)	TP	FP
Negative (not retrieved)	TN	FN

Accuracy

A model's or algorithm's accuracy is a metric that shows how well it functions and how well it was trained. In the terrain



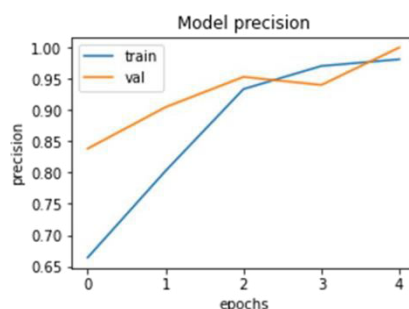
of this thesis, accuracy tells how well it's performing in detecting humans in submarine terrain. The following formula is used to determine accuracy.

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

Precision

It denotes the rate of positively predicted cases that are actually positive. In the terrain of this thesis, perfection measures the bit of objects that are predicted to be brutes and are actually brutes present in estate terrain. The following formula is used to determine precision.

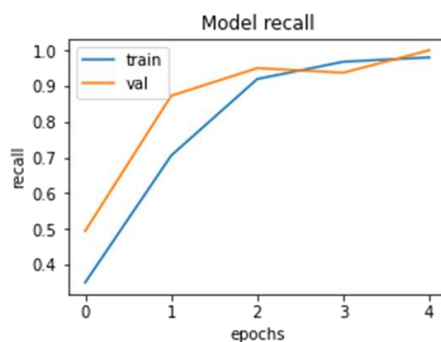
$$\text{Precision} = \frac{tp}{tp + fp}$$



Recall

It's the rate between factual positive cases that are prognosticated to be positive. In the environment of this thesis, recall measures the bit of creatures that are prognosticated as creatures. The following formula is used to determine recall.

$$\text{Recall} = \frac{tp}{tp + fn}$$



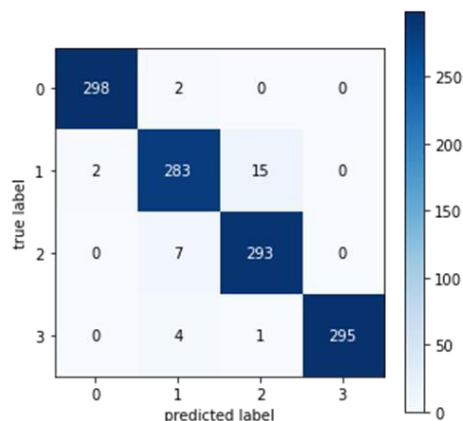
F1 Score

It's also known as balanced F- score or F- measure. F1 score is a measure of delicacy of a model combining perfection and recall. In the environment of this thesis, a good F1 score shows that there are less false cons and false negatives. This shows that the model is rightly relating creatures in ranch terrain. If the F1 score is 1, a model or algorithm is deemed perfect. It's calculated using the following formula.

$$F1 = 2 \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \right)$$

Confusion Matrix – Training

Confusion Matrix -Testing



Accuracy: 0.9984025559105432

Precision: 0.9990234375

Recall: 0.9964285714285714

F1_score: 0.9977122020583142

Training Time:

Training time is metric used in this thesis to measure the time taken to train the named machine literacy algorithms on the dataset.

Execution Speed:

Speed is a metric used in this thesis to measure the time taken for the algorithms to reuse and describe handicap.

Loss Function:

Loss function, to perform point matching between the ground truth and the output of segmentation network, optimizing also the network weights on features uprooted at multiple judgments rather than fastening just on the pixel position.

VII. CONCLUSION

Agrarian estate security is extensively demanded technology nowadays. In order to negotiate this, a vision-based system is proposed and executed using Python and Open CV to detect intruders. The performance of the proposed system has been analyzed with separate to the captured images of the intrusion and advertisement alert. Using this proposed model, anyone can describe any type of intrusion around the field effectively.

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