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Object Detection In Infrared Images Using Convolutional Neural Networks

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Abstract: In the recent couple of decades, most of the research is being done on Object detection. It is one of the most important problem in the field of computer vision having wide range of applications such as surveillance, security, medical applications etc., the researchers have been focussing on coloured images where lighting is an important factor for colour images. But, the major security issue arises in the darkness where surveillance plays an important role during the night time only. Therefore, it is essential to capture a scene in the darkness and detect the objects. Infrared imaging plays a vital role during darkness also. Such techniques shall be helpful at night navigation for military and civil areas. But, the IR images are prone to illumination effects low-resolution etc. In recent years, most of the research work is being integrated with an additional technology called night vision for surveillance cameras have built-in IR based imaging capabilities. Hence, in this paper we made an attempt to present an effective model for object detection in IR images using Convolution Neural Networks. Model is evaluated using various quality metrics, tested on different environments like CPU, Google COLAB and GPU and the results are tabulated.

***Keywords*:** Convolution Neural Networks, Infrared Images, ReLu, Softmax, Object detection.

I. Introduction

Object detection has gained importance in recent years as it has a wide area of applications which include image retrieval, driver assistance systems, security, surveillance and medical applications[1][2]. Object detection is the process of finding real-world objects in a given image or group of images or videos. In the field of surveillance and security object detection plays a vital role. Most of the existing technologies use normal RGB images to detect an object. Light plays an important role in the case of colored images. As the focus is on surveillance and security, image capturing may also be in the absence of adequate light. Images that are captured in this scenario should be used for object detection, classification. Infra-red images play an important role in such scenarios. Infrared imaging and thermal imaging [3] plays a vital role in darkness. Everything emits rays due to the heat produced in the body which is invisible to the naked eye. These rays are infra-red rays which fall beyond the visible spectrum i.e. above 0.750μm. IR radiation is divided into 3 smaller regions: 0.750 - 3μm near-infrared, 3 - 30μm mid-wave infrared, and 30 - 1000μm far-infrared radiations respectively. Near Infrared are reflective in nature and they have commonalities with visible light. The earth body emits infrared radiation due to molecular action. To capture these radiations IR night vision cameras are used [4]. These cameras can capture near-infrared images as their spectrum falls close to the visible spectrum. But the images thus captured may not be of required resolution and quality. So Convolution neural network is adapted for processing these images for object detection [5] [6] [7]. Infrared imaging is an effective technique [8] of capturing the infrared light from objects and converting it into visible images interpretable by a human eye. There are 3 different spectrums called Low-wave Infrared, Medium-Wave Infrared and Long-wave Infrared spectrum. The Far-Infrared or Long-Infrared spectrum range of the electronic spectrum is 9μm – 14μm. As most of the objects emit radiation above absolute zero, they tend to radiate due to warm boiling blood which is captured by the camera. The near-infrared signals are widely useful to the military services and the other users of the Night/day surveillance cameras [9]. In recent days, the usage of IR images is even in unmanned aerial vehicles, small moving object detection [10]. Hence, it is very much essential to develop effective techniques to detect the object in IR images more precisely. The concept of infrared emerges from the concept of heat liberated by the objects which are emitted around wave length of 0.9-14 micro meters. Due to the heat difference between objects and the environment this method of detection can be used in various areas like underground, in ocean waters. The history of infrared radiation corresponds to early 1800's .This is basically used in wars to identify enemy fleet. To note a point short wave length images produce black and white hues. High ranged infrared rays are used to form thermal images. Thermography is a branch where information about infrared images can be found. Several cameras are operated based on light, if there is light the shadow of a light ray is captured but, in low lighting conditions and in scenarios where light can't reach it is impossible to locate the objects. But in case of infrared images operate on basis of temperature. Infrared is just a part of the electromagnetic spectrum. Infrared images are always monochrome. Calcho genecide is a chemical which can be as a filter to form a infrared image which is also used in night vision glasses. The film receiving the infrared image must have antireflective, because one need to capture the heat difference and it should be written as a pattern on the image .This often increases the complexity of forming a infrared lens. The main principle utilized in formation of a infrared image is black-body radiation. In dark scenarios where ordinary cameras can't be used infrared detection can be used. In the phase of detection the entire surface with zero heat emission will be marked as black pixels and that of higher radiation will be marked with red surface and the markings will be ranging between red and black with the amount of heat released .This entire phase is done by a infrared sensor. The main principle involving is that most bodies absorb most of the radiation from visible spectrum reflecting the infrared rays. Similar work proposed on infrared rays with entropy based fuzzy set model to detect the edges overcoming one of the major limitations in which very low lighting conditions with low heat emission can result in loss of data. The limitation is solved by a method involving calculation of entropy has been depicted to determine the error rate between predictions and reality. Through infrared images we can obtain the structure or interior of a source but the colors depicted in the pictures cannot be mapped to the spectrum to get original colors. A method to increase the contrast of a infrared image such that the structure of an object can be clearly shown can be proposed to identify features in infrared images by using convolutional neural networks by considering the rotation , position ,contrast invariances of the images. Especially when moving objects are to be recognized even when in motion , which accounts for lot of underwater vessels and big fleets.

Any unidentified structures are to be identified since the data on every object varies with respect the surrounding temperature it is suggested to maintain a constantly scrutinizing neural network to identify existing objects and eliminate noise. In this scenario one need to scrutinize entire area by sending infrared rays which are reflected from the surface providing the path between sensor and the object is clear without any infrared insulators. Any aerial view infrared images can be scaled to know the intensity of the situation. Infrared images can be used to detect the problems in nuclear reactors. Nuclear reactors have a tendency of overheating, but the problem is that the heating occurs at the core of the reactor in such scenarios the core becomes the object of the infrared image. In the scenario of a underwater vessel the general temperature is maintained around 39 degree celcisus. The ocean temperatures range around 16-60 degree celcius, inside a submarine the temperature around oxygen pumping chamber reaches around 50 degree celcius. So infrared imaging can be used in such scenario. The issue with infrared images and objects is that targeting a particular object constantly is not possible .When an object is in motion and comes in contact with another object with similar heat signature the target is changed to the second object. An advantage of using infrared images in underwater vessels is that the vessels constantly are heated to maintain the heat loss to surrounding water. Since there is a constant heat loss to the surroundings, the easiest way of identifying a underwater object is only through infrared images. In case of forest fires satellite images pickup the pictures , increasing the probability of identifying the extent of reach of fire. To identify if a person is sick or not , to identify the temperature in a living body , to classify the category of species based on their average body temperatures , thermography is used , in turn uses infrared images as a means to process the information. Due to fewer wavelengths the infrared rays in active infrared systems can't travel through large obstacles which are heat resistant. Heat insulators cause much damage, making it impossible to detect objects .This condition is present in active infrared systems they are usually black and white patterns formed as an image. These systems can be monitored from short ranges .Where as high wavelength infrared images make it possible to detect and convert incoming radiation into heat signatures making it possible to develop a heat map to identify objects in larger distances. Active systems are much more stable and reliable when come to thermal imaging systems .The due difference to be noted is that infrared rays are the main principle behind thermal and infrared imaging but to applied according to distance between the object and sensor and effectiveness of the system in the suited environment.

In this paper an algorithm is determined to classify various infrared images and to identify various objects in them. A video is taken into consideration and is split into frames , The video is a composition of infrared images .Video considered runs about 45fps-120fps forming about 7200 images per minute. This is often a step when processing any video. To run the video after obtaining the images, are sent as input to a seven layered convolutional neural network, generally the neural network identifies the images based on the trained images. The model has predefined weights trained with images form a standard dataset. To improvise, expanding the number of layers is suggested as a solution. The system is trained such that is can identify many objects. This architecture is evaluated with various evaluation metrics such as purity, precision, recall and accuracy, sensitivity, specificity while testing against a standard dataset such as FLIR. This architecture provides a basis for further experimentation on infrared videos .The input of the neural network is the infrared images obtained from the data set, the weights for the model are designed. The output of the model is processed in such a way that it can classify the images into respective classes; the labels of the classes are identified by the weights of the neural network. The testing is done with the developed neural network and the above mentioned parameters are calculated . The description of FLIR dataset is as follows annotated and non-annotated RBG infrared images. The frequency of each video is 30hz. The framerate is mostly limited to 2fps videos are presented as 30fps. There are >28k, person images, >46k car images . >4k bicycle images etc.., 60 percent of the images are in day condition and 40 percent are in night condition. Thermal 8-bit JPEG is the data set file format along with the support to formats like thermal -14 bit -TIFF images and JSON annotations. A total of 14K images and along with over 10K images from video feed are processed in the dataset and is used for training the model and testing. It is mostly used in advanced driver assistance systems.

II. Related Works

IRT has the capability to record and detect radiation in the long-wavelength infrared range of the electromagnetic spectrum[11]. A sophisticated Convolutional neural network (CNN) is trained for detecting extremely low-resolution targets. [12] mentions the various advantages of using Near Infrared (NIR) images and its diversified applications like crop stress, pest infestations, video surveillance etc. As mentioned NIR has properties similar to visible images as NIR spectrum has wavelength near to the radiation of visible spectrum. In NIR band the surface reflection is material dependent.

An integrated approach is proposed [13] which use deep multi- scale CNN to do spectral transfer of NIR to RGB images. This paper also focuses on the advantages of using NIR cameras over RGB cameras in driver assistant systems- filters are not required for the sensors and infrared light beams can illuminate even in low light conditions.

Due to the significant improvement in infrared sensor technology as mentioned in [14] it is been used in surveillance products for tracking and detecting tasks. New labelled datasets started to emerge of Infrared images and video sequences. So a technique for classification using deep neural networks has been proposed in infrared images.

Brehar et al. [15] proposed a Deep Learning approach in which training is done on images without any modifications and on images that have been improved by applying enhancement methods – Histogram Equalization (HE), Contrast Level Adaptive Histogram Equalization (CLAHE), and Atmospheric Scattering Enhancement (ASE). The performance of the Deep Learning approach is evaluated using the intersection over union metric.

A real time system for Crime Scene Evidence Analysis, which can detect objects related to indoor environment, is proposed [16] which uses Faster R-CNN algorithm. The proposed system uses VGG-16 network and Region Proposal Network for object detection. The proposed architecture gives higher level of accuracy than the existing models. A new deep learning architecture is proposed [17] which hyper tunes the network and the input as two band data (NIR and red). These two bands are required as NDVI computation requires them. Types of vegetation are the dataset taken for experimentation. The proposed work utilizes only Near Infrared (NIR) and red band information for classification. The three different networks used are Alex Net, Conv Net, VGG.

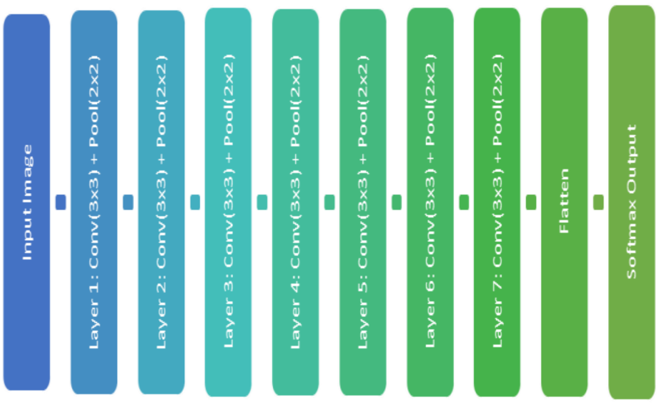
An automatic method to detect anomalies in thermal images is proposed [18] based on deep CNNs. The CNN model is trained to predict a thermal image from its corresponding visible image. Infrared thermography is gaining importance due its high precision and can be used for non-contact diagnostic. Due to the availability and affordable price of commercial thermal imaging cameras, IRT has been employed to detect temperature-related anomalies in building inspection, civil engineering, high/low voltage installations, mechanical installations and medical diagnosis.

An effective image fusion method is proposed [19] that use a deep learning framework to generate a single image that has the features of visible[26] and infrared images. A novel and effective fusion method is proposed based on a deep learning framework for infrared and visible image fusion. The fusion method preserves more detailed information and contains essential features. The proposed method results when compared to existing methods look more natural.

An infrared small target detection method based on deep learning is proposed [20]. This system is proposed due to the oversampling imaging characteristics. This system is widely applied in space remote sensing imaging and infrared search and tracking (IRST) systems like the midcourse space experiment satellite SPIRIT-III payload, a new generation of infrared scanning point-source detection space sensor and the SPOT-5 remote sensing satellite. Geng et al. [21] suggested a model to identify human movements, focused on the enhanced YOLO-V3 network involving a saliency map as the second input channel to facilitate the reuse of features and increase the network efficiency. To further validate the feasibility of the proposed process, author learned and evaluated the proposed neural network model using pure RGB images, pure infrared images, and saliency thermal picture pairs. Qingju Tang et al [22] implemented fractional Darwin particle swarm optimization algorithm (FODPSO) to recreate infrared picture sequences. author found out that FODPSO has an significant property: an integer-order calculus represents a finite sequence, and a fractional-order calculus represents an infinite set. Therefore, integer-order calculus is a local operator, and fractional-order calculus is a reflection of all past states, and as time goes by, the power of past states is slowly diminished. Z. Gao et al [26] observed that the transfer-learned neural network such as MobileNet could extract more information from infrared images than the original network could. In order to identify the most important features in an infrared image, the opening and closing operations can be used as the primitives at different scales. The two most common databases comprising recorded pairs of infrared and visible photos Kayak and TNO are used. S. Chen et al [27] proposed a novel fully convolutional neural network (Nv-Net) model for the low-resolution infrared images in weak illumination natural environments. Mean-variance normalization pre-processing is adopted to accelerate the network convergence.. Low illumination image dataset (LII) is used to train and test model and evaluated by using a metric called Interaction-over-Union (IoU). Qiu et al. [28] developed a method for moving target detection and monitoring in infrared and natural images. It is based on the conventional frame difference system. The rough entropy principle used to separate moving regions from the viewpoint of electricity. To merge features of infrared images and visible images, author creates a full flow map of moving target detection and tracking algorithm based on infrared images and visible images. B. Wang et al [27] studied the problem on the edge detection of infrared image. A novel approach is developed to achieve the edge detection of infrared signal by using the properties of the Spiking Neural Network (SNN) which has the efficient computational capabilities, which is also good for visual information processing with high-voltage insulator used to show the efficacy of algorithm. Wang B et al [28] experimented on the contract enhancement of infrared picture and memristive mapping was coupled with PSO to evaluate parameters adaptively. PSO will calculate the coefficients efficiently, but the presence of inertia weight render PSO hard to fulfil the detailed output criterion for high inertia weight which allows PSO has low local searching efficiency, and small inertia weight makes PSO simple to leap into the local optimum. MPSO algorithm involves measures Normalization, Memristive mapping, Reverse mapping, and Measure performance. The efficacy of MPSO algorithm is checked by high-voltage switch infrared signal.

II. Proposed CNN Architecture

Figure 1. Convolution Neural Network Architecture



The above Figure1 shows the proposed CNN architecture. The input is an image of size 640 * 480 Infrared image. The architecture is designed considering the fact that the image is prone to illumination, low resolution and other effects which becomes difficult for the image to process and detect the object accurately. Hence, in this architecture, we have Seven Convolution layers with max-pooling and One Flatten and finally the Softmax activation function. The initial convolution layer uses 32 filters and rest of the Six hidden layers use 100 filters of size 3 x 3. At every layer, Max-pooling is also performed with a scale of 2 x 2. The convolution layers are then flattened and is normalized through Softmax step. The activation function used at all the layers is “ReLu”.The shear is 1 and stride as 1.

III. Experimentation:

The experimentation has been carried out on three different environments. The entire work has been implemented using Keras and is tested with two different dataset of size 189 images and 147 images later is tested on GPU with even 1820 images. The datasets considered are FLIR and initial experimentation has been done on a system with a CPU of Core i5, 8 GB RAM and 1 TB HDD. Later the experimentation was done on NIVIDIA DX-1 GPU with 128 GB RAM and speed of 1 Tesla.
The experimentation was done using the dataset of 147 image and 189 images having 7 different classes and 21 images and 27 images respectively per class. Figure2 and Figure3 clearly represents the accuracy and efficiency of the model with two sets. Figure4 and Figure5 shows the evaluation metrics.
The sample image in each class is shown below. (put 7 images as 1column, predicted as 2 column)

The proposed model is evaluated based on various evaluation metrics
such as Precision, Recall, F-Score, and Accuracy, which are defined as,
Precision = TP / (FP + TP)
Recall = TP / (FN + TP)
F1-Score = (2 * Recall * Precision) / (Recall + Precision)
Accuracy = (TP + TN) / (TP + FP + FN + TN)

Object	Accuracy
Building	0.952
Car	0.950
Corridor	1
Head	1
Keybobrad	0.952
Officedesk	1
Pens	1

*Table 1.*Accuracy for each class for 147 images

In the above table the results are tabulated based the accuracy obtained by experimenting on 147 images with 7 classes in which the model predicted correctly with high accuracy for Corridor, Head, officedesk and pens.

The respective confusion matrix for seven classes with their TP(True Positives), TN (True Negatives), FP(False Positives) and FN(False Negatives) is given the following table

	PREDICTED						
	Building	Car	Corridor	Head	Keyborad	Office desk	Pens
Building	26	0	0	0	0	0	0
Car	0	26	0	0	0	0	0
Corridor	1	0	27	0	0	0	0
Head	0	0	0	21	0	0	0
Keyborad	0	0	0	0	26	0	0
Office desk	0	1	0	0	0	27	0
Pens	0	0	0	0	1	0	27

Table 2. Confusion matrix for 147 images each class with 21 images

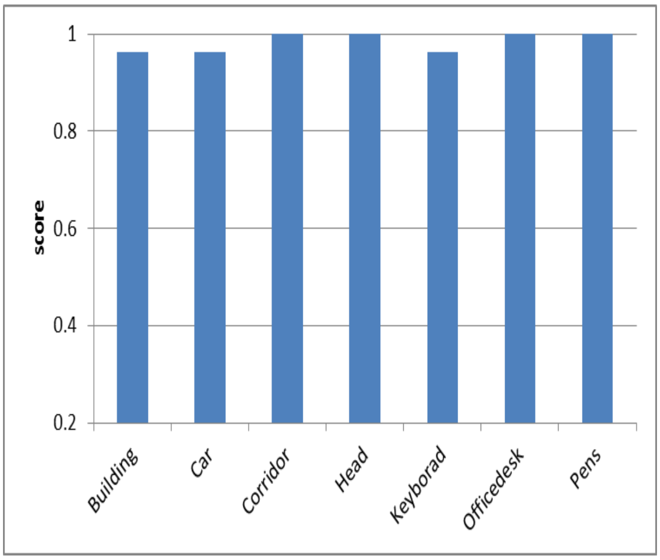


Figure 2. Accuracy for 147 images each class with 21 images

Object	Accuracy
Building	0.963
Car	0.963
Corridor	1
Head	1
Keyborad	0.963
Officedesk	1
Pens	1

Table 3. Accuracy for each class for 189 images

	PREDICTED						
	Building	Car	Corridor	Head	Keyborad	Office desk	Pens
Building	20	0	0	0	0	0	0
Car	0	19	0	0	0	0	0
Corridor	1	0	21	0	0	0	0
Head	0	0	0	21	0	0	0
Keyborad	0	1	0	0	20	0	0
Office desk	0	0	0	0	0	21	0
Pens	0	1	0	0	1	0	21

Table 4. Confusion matrix for 189 images each class with 27 images

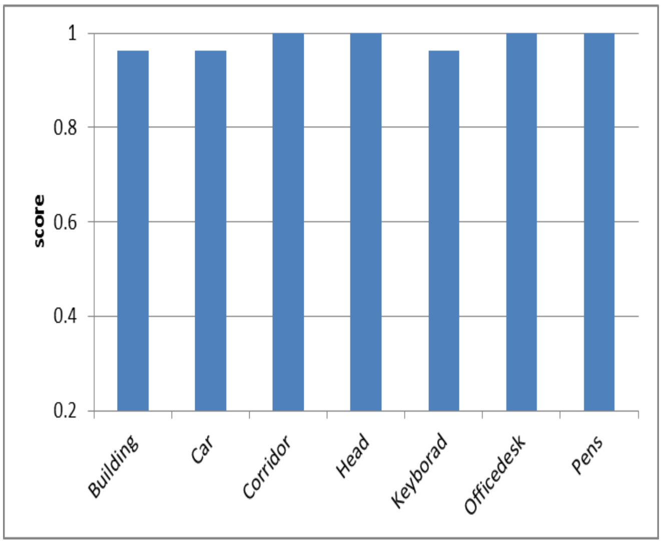


Figure 3. Accuracy for 189images each class with 27 images

Table5 shows the evaluation metrics for each and every experimentation done on three different environments.

Experimental Epochs	Sensitivity	Specificity	Precision	F-Score
1	0.86	1	1	0.96
2	0.87	1	1	0.93
3	0.93	1	1	0.96
4	0.94	1	1	1
5	0.93	1	1	1
6	1	1	1	1
7	1	1	1	1

Table 5. Evaluation metrics for 147 images each class with 21 images

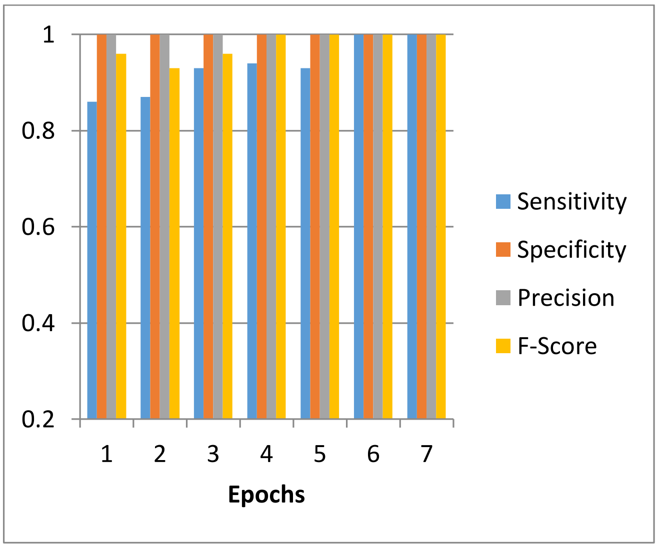


Figure 4. Evaluation metrics for 147 images each class with 21 images

Experimental Epochs	Sensitivity	Specificity	Precision	F-Score
1	0.92	0.94	0.80	0.93
2	1	0.82	0.87	0.86
3	0.87	0.87	0.97	0.87
4	0.93	0.94	0.97	0.98
5	1	0.93	0.93	0.98
6	0.93	0.93	0.97	0.98
7	1	0.87	0.87	1

Table 6. Evaluation metrics for 189 images each class with 27 images

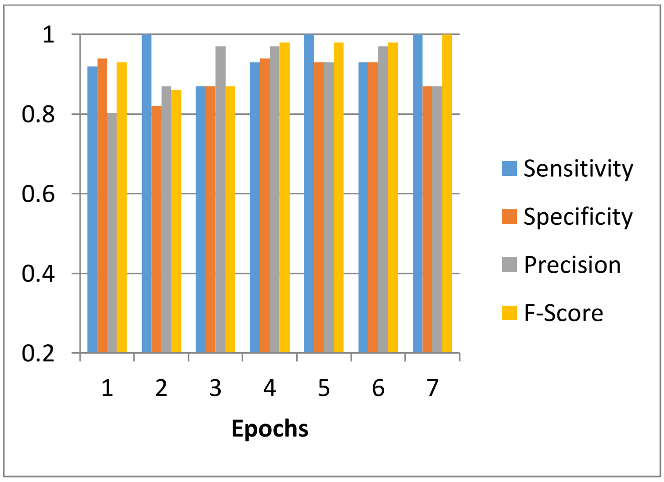


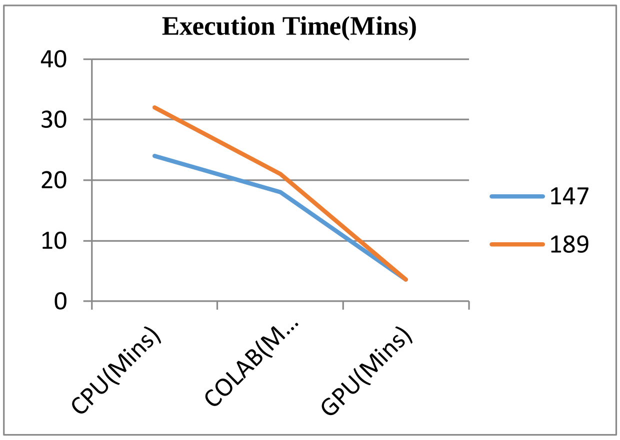
Figure 5. Evaluation metrics for 189 images each class with 27 images

Figure 6 and *Table 7* shows the graph of performance of the proposed model on three different working environments. It is found that the experimentation time is observed to be very less on NIVIDIA GPU when compared CPU and COLAB's GPU.

#Images	CPU(Mins)	COLAB(Mins)	GPU(Mins)
147	24	18	3.6
189	32	21	3.6

Table 7. Execution Time for three environments

Figure 6. Execution Time for three environments



IV. Conclusion & Future Works

The advent of IR images shall help in utilizing in various security and surveillance areas. The experimental results clearly speak that the accuracy of the proposed CNN architecture outperforms in terms of accuracy and the usage of GPUs shall reduce the processing time by 90%. Hence, the proposed model has given much accurate results. However, there is further scope of improving the by recognizing the object and identifying the object. Also, it is essential to understand the scene. The same work can be extended to identify the objects in underwater images which will be useful for the defence

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Dr Suneeth Kumar Guptha is currently working as a Professor in the Department of Computer Science Engineering at Bennett University, Gr.

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