Foreign Object Debris and Surface Defect Detection at Airport Runway

Chavan Shubham
School of Computer Science
MIT WPU, Kothrud.
Pune, India.
shubhamcwork@gmail.com

Katare Shlok
School of Computer Science
MIT WPU, Kothrud.
Pune, India.
shlokkatare1898@gmail.com

Mane Tanmay
School of Computer Science
MIT WPU, Kothrud.
Pune, India.
tanmaymane8@gmail.com

Vaidya Suvarna
School of Computer Science
MIT WPU, Kothrud.
Pune, India.
mail.vaidyasuvarna@gmail.com

Khule Shubham
School of Computer Science
MIT WPU, Kothrud.
Pune, India.
shubham99.khule@gmail.com

***Abstract* — Aviation industry is huge with rapid expansion and growth in both passengers as well as flights. While runways are being constantly used, certain steps are needed to be taken care of it so that delays/accidents are avoided. Since the major causes of the same are foreign objects, bird strikes and surfaces defects, manually assessing and monitoring the entire runway is a tedious task which also could cost a lot and still is not as accurate. Hence, there is a need for automation of the entire process. Image processing, ML and DL techniques have been used to achieve a single solution for all the problems mentioned.**

In our paper, we propose a system based on computer vision to detect FODs as well as surface defects which is continuously being monitored and so is much more cost efficient than the manual process as well as detects and classifies all the objects and surface defects successfully.

Keywords—Machine Learning, Deep Learning, Foreign Object Debris, Computer Vision.

I INTRODUCTION

The aviation industry is rapidly expanding with consistent growth in passengers as well as cargo flights. In 2017, airlines carried 4.1 billion passengers while also transporting 56 million tons of freight on 37 million commercial flights.

Around 10 million passengers and goods worth 18 billion USD are transported by airplanes every single day. These numbers are further expected to double in the next 15-20 years.

Building new infrastructure or expanding existing airports is time-consuming and thus, becomes paramount that the current infrastructure can handle the traffic growth. To achieve the same, the handling of commercial flights has to become more efficient by reducing delays and optimizing related operations.

With several reasons behind delay are runway related. Some major ones being foreign objects, bird strikes, surface defects, etc.

Foreign object damage is a common risk for the aviation industry since a long time ago and it has contributed to many terrible incidents and fatalities like in 2000 Air France flight 4590 crashed only due to a small metal strip which resulted in in-flight fire and loss of control. The metal strip was from a continental flight which had taken off from the same runway minutes ago. The cost of foreign object damage cases every year is very high, which is around RM 1.2 billion Foreign object damage [1] occurs mainly at runways, taxiways and gateways. In less likely situations, aircraft tiers and even engines get damaged if ingested by those objects which causes substantial delays in multiple aircraft.

Based on a previous French study on automatic object detections, over 60% of the foreign objects collected were made of metal while 18% made of rubber. Eg: engine fasteners like nuts and bolts, aircraft parts like tyre fragments and fuel caps, etc.

All the above depicts that foreign object damage to the aviation industry. Similar damages are also caused by bird strikes and other such animal impacts.

To avoid all the damage caused by foreign objects, real-time and accurate foreign objects debris (FOD) detection can be an effective solution to ensure safer flights.

Traditional methods like infrared multi-beam detector, laser-based detector, radio-waves based detector,

video sensor-based detector has been used. These methods have been limited by cost prohibition and limited effectiveness. They also required a lot of experience, special knowledge of field and data and were often limited by the algorithms that they used.

Another major potential cause of FOD's being present on the runway can be the runway itself. Through consistent use and harsh weather conditions, defects occur such as cracks, bleedings, depression, spillage, patching, etc. Which is currently monitored through regular manual inspections which are time-consuming also requires expensive manual labor.

With the advent of computer vision, faster processing capabilities, better cameras, and advanced machine learning solutions like DNNs it has become possible to perform object detection tasks with much more preciseness.

Detection of FOD's and both surface and subsurface defects is a vital task for maintaining the structural health and reliability of airport runways. We propose a novel system, which employs a camera to inspect the airport runway to detect FOD's and surface defects. This paper presents a solution to this important problem faced by the aviation industry.

II Problem statement

Airport runway monitoring is a highly important yet a very challenging task as FODs and surface defects can be of any size. Therefore, the proposed system must be able to perform FOD detection task with high efficiency, should be able to work with minimum human intervention and it should cover the entire runway to ensure safety for the aircraft as well as passengers. The system should also be capable of alerting the concerned authorities whenever FODs are detected so that corrective action can be taken on time.

Detailed work needs to be carried as to what computer vision-based FOD detection systems can be implemented to provide the best possible solution to the problem of FOD detection. The combinations of technologies to be used should be effective, comprehensive and have built-in redundancy to ensure smooth operations. The system should also take into account different weather as well as lighting conditions. The system should also be sufficiently flexible and designed using off the shelf components.

III LITERATURE SURVEY

FOD is any object live or not, located in an inappropriate location in the airport environment which can injure airport personnel, aircraft or airport infrastructure. It poses a severe risk to cause catastrophic failure [2].

Hussin et al in "A study of foreign object damage and prevention method at the airport and aircraft maintenance area" [1] argue that due to dangers of FOD, the stakeholders of the aviation industry need to take effective steps to ensure FOD detection and prevention. It was argued that while there are no full-proof solutions and there will never be a 100% FOD free area, the time in which the FOD's are detected and removed can be continuously improved.

The different types of foreign objects which pose a problem to the aircraft were studied in a survey on

foreign object debris and foreign object damage prevention by aviation maintenance and manufacturing. The survey mentioned the different sizes of debris involved and the different approaches to detect them such as radar and high-end cameras along with manual human surveillance. It noted the high cost of the mentioned systems. Thus, a good computer vision system is being proposed.

FOD detection using sensors mainly includes three different approaches: laser-based detector [3], infrared multi-beam detector [4] and computer vision (video-sensor) based detector [5].

Using Computer Vision, XuKyunye et al, in 2009, proposed a fallen object target detection algorithm based on image change detection in their paper "video-based foreign object debris detection" [8]. The paper, however, failed to consider the variation in image quality due to changes in environmental conditions. Even, still, they managed to introduce a novel idea in the field of FOD detection by using Computer Vision techniques.

The PSNR and SSIM Objective image quality metrics were analyzed by Alan Hore et al in their work [9] to study their extent in rectifying noise component of an image. Histogram and gamma corrections were used for contrast assessment and enhancement. This approach was further improved by Dongni Zhang et al [10] when they proposed local gamma correction through histogram analysis for image contrast enhancement. Based on the local minima, image histogram is partitioned and the mean grey level is calculated for each partition. These mean grey levels were then used to perform gamma correction.

In another paper [11], Contrast limited adaptive histogram equalization (CLAHE) method was used to enhance surveillance videos affected by fog and rain.

The detection of moving objects was studied by Kai Liang et al [12]. By identifying the orientation and centroid of the moving object, they used variation temporal differencing for moving target detection.

Jayadharani et al in “Foreign object detection using hybrid assessment and enhancement technique” [13] proposed a method to detect foreign object effectively under different environment and lighting conditions. They employed several image enhancement techniques to enhance the image after first assessing it’s quality. Further, objects were detected and also classified as static or moving. Image histogram distribution, SSIM and PSNR were computed to analyse the image deterioration by fog, noise or illumination. Gamma correction, CLAHE and Wiener filter for rectifying the images. After the entire process, edge detection has been used for image segmentation with temporal differencing being used for moving object detection.

All the approaches to object detection up until then involved image processing using myriad different methods. With the advancements in Computer Vision technology and the Machine Learning algorithms such as Neural Networks, they were now employed in the field of object detection.

Computer Vision has rapidly improved FOD detection through rapid image segmentation reducing the time taken [6]. These systems have rapidly evolved to form a strong base of well-performing object-detection systems. Within the Deep Neural Networks, there are 2 types of systems that have come into existence: i) 2-stage methods, ii) 1-stage method.

In the 2-stage system, the problem of detection has been divided into two parts, the first step extracts a series of likely proposals and the second step then classifies these extracted set of proposals. For feature extraction, CNN’s have shown a good performance. As a result of this, R-CNN uses CNN for this purpose. When compared to the traditional detection methods, R-CNN displays an improved accuracy. This was further improved upon to a great extent by Fast-RCNN which was based on VGG16 [7]. Fast-RCNN was 9 times faster than R-CNN in training and 213 times faster in testing.

The 1-stage method takes the divided process of the 2-stage system and combines it into a single stage using the idea of regression. They take the whole picture as input and the classification and regression are carried out at the same time which reduces the computing time required. YOLOv1 utilised this idea to detect objects in a faster way, however, it lacked accuracy. Built using GoogleNet [14]’s structure, it combined the 2 step process of region proposal and object recognition and was almost real-time. SSD borrowed the ideas of Faster RCNN and YOLOv1, utilized multi-layer feature information to improve the speed and accuracy. YOLOv2 [19] used k-means clustering on training data for setting better anchor priors while Retina-Net [15]

used the focal loss to try to solve the imbalance problem in object detection. Using these and more such ideas, performance and prediction accuracy were further improved by YOLOv3 [16] and Gaussian-YOLOv3 [17]. CenterNet and FCOS[18] were implementations of anchor-free methods. FCOS uses semantic segmentation to solve the problem of object detection via pixel prediction.

Yunkai Liu et al in their paper titled “FOD Detection using DenseNet with Focal Loss of Object Samples for Airport Runway” [20] further proposed a method to detect small size FOD’s using Convolutional Neural Networks. They employed Faster R-CNN framework to generate candidate regions for the input image. Also, DenseNet was used instead of the traditional VGG16Net for feature extraction, which greatly reduced the network parameters and benefited to small-scale FOD detection.

Automating Surface Defect detection is a relatively new venture and active research is being made in this field. Recent advances in vision-based, automated pavement crack detection techniques include intensity-thresholding, match filtering [21], edge detection [22], seed-based approach [23], wavelet transforms, texture-analysis, and machine learning. An automatic procedure for crack detection known as CrackTree was proposed by Zou et al. [24].

Machine Learning models have been used for pavement distress detection with varying degree of success. Consequently, deep learning models are now being applied to solve the problem. Zhang et al. developed a crack detection model using raw image patches via the CNN-based software CrackNet [25]. In 2019, Zhang et al.

implemented the Recurrent Neural Network (RNN) technique to create CrackNet-R, which is more efficient than CrackNet in detecting small cracks and in removing noise [26]

IV AIM

To develop an automated FOD and Surface Defect detection system that utilises Computer Vision with Image Processing backed by Machine Learning to work in varying environmental and lighting conditions.

V OBJECTIVES

A camera system of appropriate specifications to be used to continuously monitor the airport runway through video surveillance.

Appropriate image/video quality assessment to be performed to determine the image quality for the specific application (FOD detection / Surface defect detection).

Post the image quality assessment, image processing operations to be performed to enable accurate classifications of the defects/debris.

The preprocessed image is to be then fed to a classifier which will perform region analysis, generate candidate regions and finally identify the objects or the defects. A bounding box(s) will be created around the detected area and concerned alerts will be raised.

VI METHODOLOGY

In the design of the FOD and surface defect detection system, the primary mode of collecting samples to be analysed and processed by the program to come to accurate conclusions is through the digital camera. The digital camera is the primary mode with which the system will interact with the real world to continuously monitor it via the video feed.

Through the data that we acquire from the digital camera, we aim to detect the presence of Foreign Objects Debris(FOD) and surface defects on the airport runway. The FOD detection system will need to work in real-time through continuous monitoring as a FOD can be introduced to the runway at any given point in time and its detection and removal have to happen as soon as possible. The surface defect detection will happen at a periodic rate so that it is effectively monitored. If any significant surface defect is suddenly generated, it will introduce FOD onto the runway which will be immediately detected by the system.

For detection of either the FOD or the surface defects, first, the image obtained from the video will have to be assessed to determine whether it is of the appropriate quality so that the proper classification can be performed on it to correctly identify the object or defect. This quality determination of the image will be done via image pre-processing techniques such as image histogram analysis, gamma correction followed by which enhancement techniques such as image histogram equalization will be used. If so desired, further image processing can be done such as background subtraction, masking, singular value decomposition.

After the image quality is determined, it is processed and enhanced, the image will be fed to the classifier. The classifier can be trained using neural networks, either 2 stages or 1 stage, depending on the effective combination of speed, accuracy, throughput as required for the application. As discussed in the literature survey, the 1 stage systems are usually faster and more accurate, however, this will have to be determined with proper training, testing and result validation.

After the object/defect is classified and detected, a bounding box is will be created around them and alarm will be raised to notify the concerned authority so further corrective action can be taken.

VII DATASET

FOD detection:

A dataset consisting of different types of FOD’s, namely, metal, plastic and concrete. Each category has 1000 samples for the training set and 100 samples for each category for validation. The dataset is representative with different types of objects as are often seen in real life. The data can be further augmented to create even more samples if required for training.

Surface Defect detection:

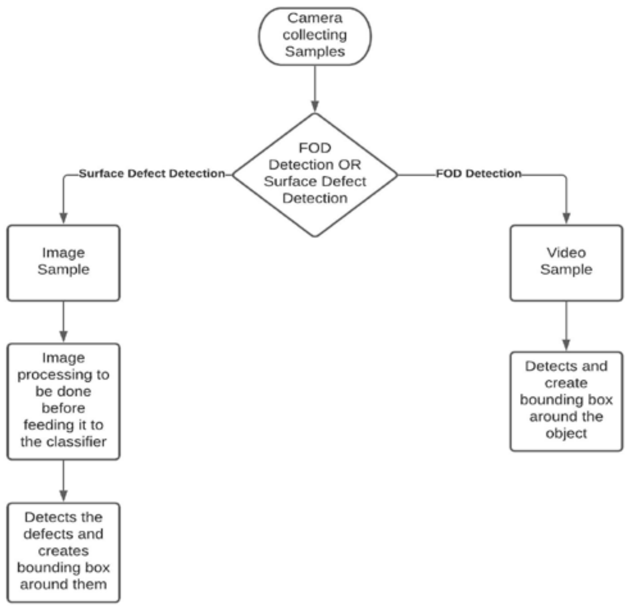
1. German Asphalt Pavement Distress (GAPs) dataset: A collection of sample images for different types of asphalt(road) surface defects. The dataset was collected in varying conditions through

manually driving on real roads with a camera attached behind the vehicle. The images are in high resolution. 2000 high-resolution images of different types of surface defects, namely, different types of cracking, bleeding, depression, holes, jet blast, oil spillage, patches.

2. Pavement Crack Detection dataset: 8000 image samples collected through Google API resembling real-life

conditions with varying image resolution. Consists of wide-angle images which can be used for deep learning frameworks to detect cracks, top view images which can be analysed for distress density detection. Collected by official pavement rating authority which has been used by different research teams.

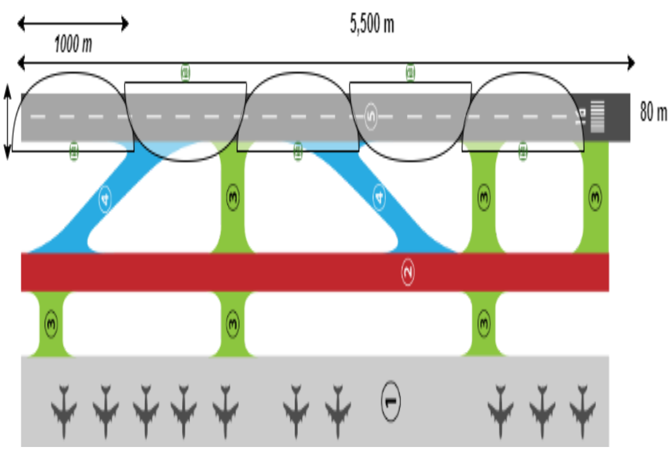
VIII BLOCK DIAGRAM



IX SPECIFICATIONS

Runway:

Dimensions vary from as small as 245 m (804 ft) long and 8 m (26 ft) wide in smaller general aviation airports, to 5,500 m (18,045 ft) long and 80 m (262 ft) wide at large international airports built to accommodate the largest jets.



DIGITAL CAMERA:

Advanced, all-weather technology for runway inspection even in inclement and harsh weather conditions. Should be able to operate in high temperatures, sandstorms, or at an airfield that encounters frequent fog, should be operational in near-zero visibility conditions.

Sensor	1/1.9 Starlight HD sensor or 1/2.8 HD Progressive Scan CMOS Sensor
Resolution	1920x1080 Full HD 12MP Ultra HD Zoom, D1 or CIF Substream
Shutter	User-defined 1/100000
Illumination	1-5km ZLID Laser IR Illumination Syncs with Zoom Lens
Operating Temp	-40~60C Extreme Weather
IP Rating	IP67 MIL-810-STD Military-grade all-weather camera system
Horizontal Field of View	Wide 85mm 8.6° Narrow 1400mm 0.5° HFOV 17x zoom
Digital Zoom	2X and 4X Digital E-zoom
Continuous Zoom	16x 85~1400mm Autofocus Zoom Lens
Extreme Weather	IP 67 water jets from all sides, -50~60C integrated heater blower, Defog and De-haze image processing integrated filters for fog penetration
Multi Sensors	Optional: SWIR, LWIR, MWIR, NIR, IR, Infrared, LRF, Starlight, EMCCD, HD CMOS, CCD Imaging Detector Sensor

When it comes to a debris monitoring system, optionally along with optical camera advanced technology millimeter wave radar detects FOD, birds and wildlife with a high level of sensitivity.

For further optimization of the system, millimeter wave radar/software combination can be utilized for continuously monitoring pavement and infrastructure. This can help detect pavement crack or change in surface height, or even the movement of an in-pavement light fixture, alerting airport operations before it becomes a hazard.

X SYSTEM ALGORITHM

1: *Contrast Stretching*: Contrast stretching (often called normalization) is a simple image enhancement technique that attempts to improve the contrast in an image by ‘stretching’ the range of intensity values it contains to span a desired range of values, the full range of pixel values that the image type concerned allows.

Before the stretching can be performed it is necessary to specify the upper- and lower-pixel value limits over which the image is to be normalized. Often these limits will just be the minimum and maximum pixel values that the image type concerned allows. For example, for 8-bit gray level images the lower and upper limits might be 0 and 255. Call the lower and the upper limits a and b respectively.

The simplest sort of normalization then scans the image to find the lowest and highest pixel values currently present in the image. Call these c and d. Then each pixel P is scaled using the following function:

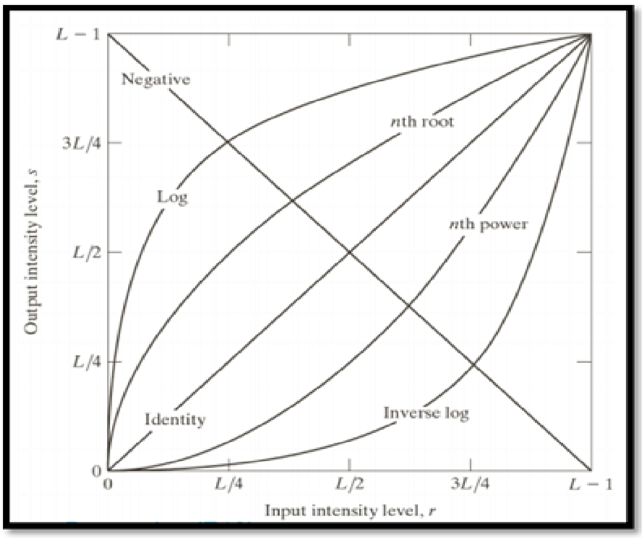
$$P_{out} = (P_{in} - c)\left(\frac{b-a}{d-c}\right) + a$$

2*: Image Rotation*: Rotation of images allows us to turn an image in a clockwise or counter clockwise direction so that we get more samples.

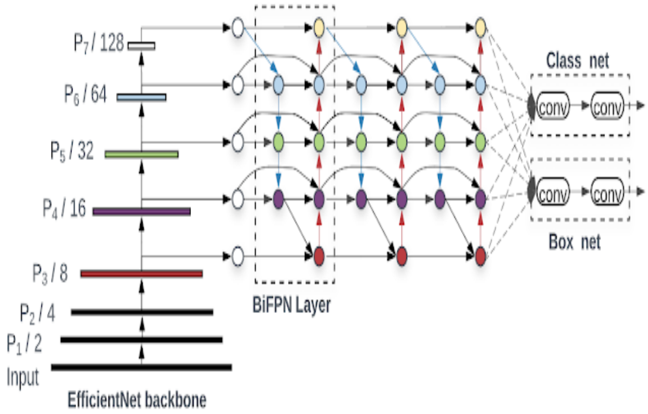
3: *Grey Scale Transformation*: It operates directly on the pixels. The gray level image involves 256 levels of gray and in a histogram, horizontal axis spans from 0 to 255, and the vertical axis depends on the number of pixels in the image.

The 3 types of transforms are as follows:

Linear, Logarithmic and Power-Law.



4: *EfficientDet D0*: EfficientDet feature fusion seeks to combine representations of a given image at different resolutions. Typically, the fusion uses the last few feature layers from the ConvNet, but the exact neural architecture may vary.



5: *Convolutional Neural Network (CNN)*: A convolution is the simple application of a filter to an input that results in an activation. Repeated application of the same filter to an input results in a map of activations called a feature map, indicating the locations and strength of a detected feature in an input, such as an image.

The dimensions of the output matrix - taking into account padding and stride - can be calculated using the following formula:

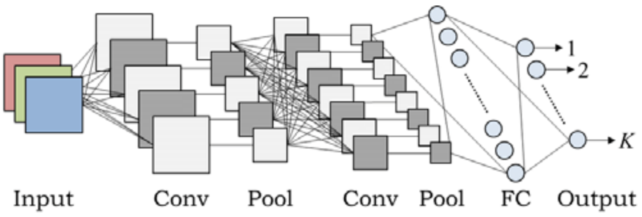
$$n_{out} = \left\lfloor \frac{n_{in} + 2p - f}{s} + 1 \right\rfloor$$

XI SUBMODULE ALGORITHM

For the purpose of FOD detection, we have proposed to train a model based on a CNN (Convolutional Neural Network) for object detection. To train the model, we are using a dataset that consists of images containing commonly found FOD’s such as concrete and metal. For effective processing of the images and obtaining satisfactory results, the images are preprocessed using techniques such as rescaling, contrast stretching. The images were then divided into the training and testing sets. Further to further increase the data available to us, image augmentation techniques such as random rotation and gray-scaling were applied to the training dataset.

For the object detection system, we are following a process of using a pretrained model from the TensorFlow model zoo. The benefit of using a pretrained model is that it is already trained on a huge dataset, thus we can avoid training from scratch and simply retrain the model on our custom dataset using transfer learning. This produces satisfactory results while saving significant amounts of training time.

We are using the EfficientDet D0 model, which has the EfficientNet B0 as its backbone.

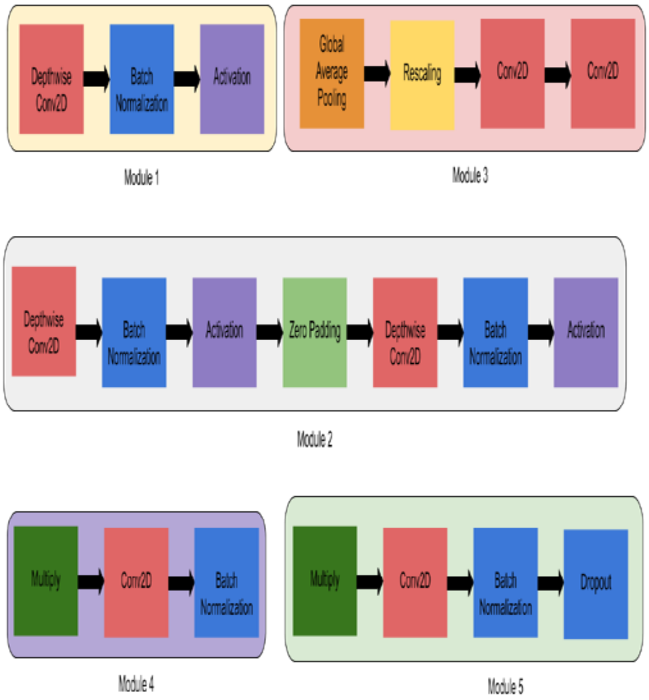


CNN (Convolutional Neural Network) is a type of Neural Network used for processing 2-dimensional data like images. They have found success in image detection and classification applications. Convolution is the mathematical operation performed on an image input I using kernel K to achieve a transformed image. These operations help us in extracting only the useful information from an image.

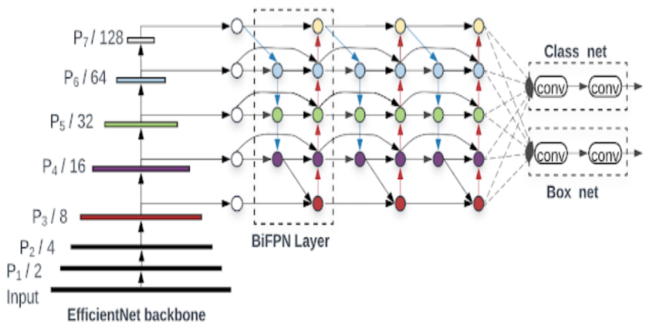
$$S_{ij} = (I * K)_{ij} = \sum_{a=\lfloor -\frac{m}{2} \rfloor}^{\lfloor \frac{m}{2} \rfloor} \sum_{b=\lfloor -\frac{n}{2} \rfloor}^{\lfloor \frac{n}{2} \rfloor} I_{i-a,j-b} K_{\frac{m}{2}+a,\frac{n}{2}+b}$$

Where,
K = Matrix representing weights assigned to pixel values, has dimensions a rows and b columns.
I = Input pixel value matrix.
S = Output matrix.

The EfficientDet family of CNN models are designed with uniform scaling in mind. In traditional CNN's, the model is scaled by scaling of its width, depth or the image resolution. These methods have bore good results but eventually reach a level of saturation and the performance drops down. With such a method of scaling, the training time of the models also increases multi-fold. That is to say that their efficiency could be improved. In EfficientNet/EfficientDet, the model is scaled by uniformly scaling its width, depth and image resolution. That is, the number of layers, number of nodes within each layer and the input image resolution are all harmoniously scaled to achieve excellent results in a much shorter training period.



A modular approach is followed in the model construction. This helps with the uniform scaling feature of the model and is its salient feature.



EfficientDet D0 consists of 237 layers, 4049571 parameters and has been pretrained on the ImageNet dataset. We will be using transfer learning to train it on our custom dataset.

Consisting of the EfficientNet as its backbone, it merges it with a BiFPN(Bi-directional Feature Pyramid Network) layer for fast multi-scale feature fusion between the layers.

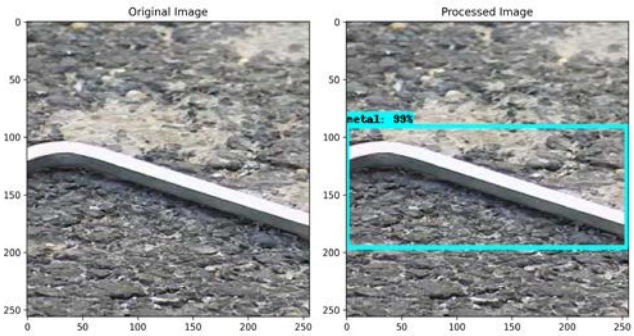
Convolution neural network (CNN), is a type of deep learning technique used for classification problems involving images. It is a combination of convolution layers and neural network layers know as dense layers. The convolutions layers are use in order to extract features from images. In this segment we will understand of convolutions are used for feature extraction. We have used resnet50 for demonstration purpose.

XII RESULTS AND DISCUSSION

FOD:

The model was trained for a total of 3000 epochs following which the loss function had significantly tapered off indicating lower benefit with additional training.

The trained model was able to successfully identify the presence of FOD's in the test images and also labelled them correctly with their classes.



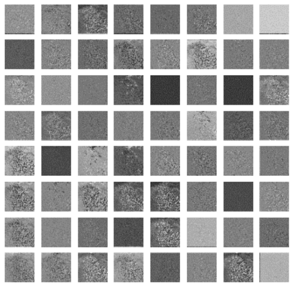
Subsequently, with the successful creation of an FOD detection model, this can be paired with an alarm raising system to notify the relevant authorities to the presence of FOD's to create a complete system. Additional training with actual airport runway images will improve the real-life performance of the system.

This project aimed at demonstrating the viability of such a FOD detection system and it has successfully done so. This can now be taken to the next logical stage by partnering with the authorities to develop a secure, real-time FOD detection system for the airport runway.

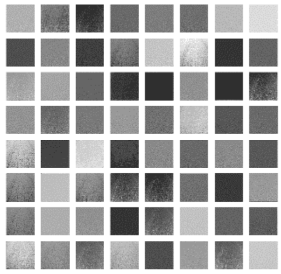
Surface Defects:

Results of layer one:

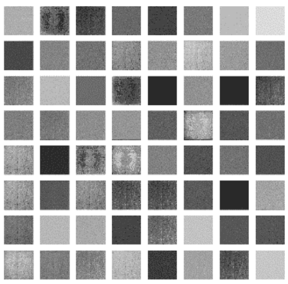
Low:



Medium:

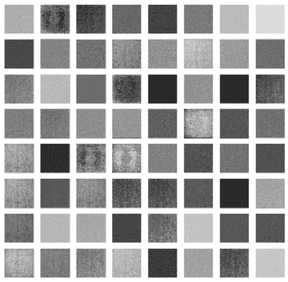


High:

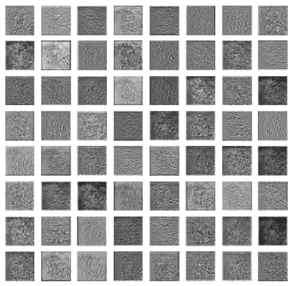


Understanding how different layers extract different features:

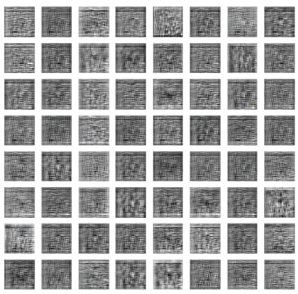
Layer1:



Layer27:



Layer 49:



By understanding the layers, we can fine tune the model according to our requirements.

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