OBJECT RECOGNITION USING THERMAL IMAGING TO ASSIST VISUALLY IMPAIRED PEOPLE.

Digital Image Processing (SWE1010)

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Abstract:

Dealing with a sight loss is a huge challenge in itself. The lack of aiding resources, the limited accessibility to activities and information, the societal stigma, lack of employment opportunities, increased risk of falls, fractures and injuries are all factors frequently leading blind or low vision individuals in reducing their mobility and social isolation. Visually impaired tools can assist them to improve their lifestyle.

Thermal sensors and thermal imaging in the recent years have proven to be versatile and effective. They have the proficiency of detecting objects regardless of the lighting conditions. Using this enhanced object recognition method, we aim to support the visually impaired people to successfully recognise objects in their surroundings by using various image processing techniques like pre-image processing, enhancing the quality of that image, image restoration, segmentation and post-processing.

Literature Review:

Muhammad Sheikh Sadi **[1]** In this study, the proposed system uses an IoT-enabled automated object recognition system that assists the visually impaired to recognize several objects and provides an audio message to aware the user. There are four laser sensors used in the system to detect the objects in front, left, right and ground. It uses Single Shot Detector (SSD) model with MobileNet and Tensorflow-lite to recognize currency note and also objects in both indoor and outdoor environments.

Kalita, R **[2]:** This paper focuses on deep learning algorithms for human recognition and their detection of RGB visible image for thermal cameras. In a YOLO algorithm, single neural network divides the given image into number of regions and then they are localized, classified and confidence score of every region is obtained. In YOLOv3, the new and improved DarkNet-53 is used and is trained on ImageNet. The previous layers are concatenated with unsampled layers thus storing all the fine features for small objects detection. Dataset used for this study is KAIST multispectral pedestrian dataset that contains images in various illumination condition. Evaluation metrics is used to find average precision and the miss rate value. An AP score of 95.15% is obtained.

Aparna [3]: The target of this work is to analyse the practicability and accuracy of thermal imaging for pothole detection. Convolutional neural networks (CNN) approach of deep learning is adopted after implementing some augmentation techniques on our data. Further, a comparison between the self-built convolutional neural model and a few of the pre-rained models has been done. A ResNet model is developed based on CNN to detect potholes. The pre-trained models are customised. These models are fine-tuned according to the problem by training them on pre-computed weights for few epochs. Then, the precomputed weights of end layers are removed and the resultant model is trained using cyclic differential learning rates and test time data augmentation. An accuracy of 97.08 has been achieved which is the best ever reported among the similar studies so far. It is inferred that YOLO detector that is trained with COCO dataset is unable to detect thermal images since they differ from the usual RGB images.

Debasmita Ghose [4]: This paper investigates into the improved performance for pedestrian detection using just thermal images, thereby eliminating the need for paired colour images. Static saliency maps using OpenCV library are used for the experiments and also to train the Faster R-CNN for pedestrian detection and report the outcome of saliency maps generated using static and deep methods (PiCA-Net and R^3-Net). The best performing model obtained gave an absolute reduction of miss rate by 13.4% and 19.4% over the baseline in day images and night images respectively. The KAIST Multispectral Pedestrian dataset at the pixel level is interpreted to be used by deep saliency networks.

Ophoff [5]: This paper proposes the fusion of RGB+Depth images using single-pass detection networks. Robust experiments are performed, so as to work out the most effective level to fuse both the information sources. A fuse layer architecture is built which is capable of fusing both streams at any arbitrary layer within the network. The outcome of the experiments has concluded that RGB+Depth fusion increases both the general detection accuracy and the localization performance of the bounding boxes, despite the depth acquisition method. The results also seem to point that mid to late fusion performs best, though there's no exact optimal fusion level. So, a further hyperparameter might be the fusion level, which should be tuned separately for each different cases.

Yeom, S [6]: A multirotor is used to capture IR thermal video that can be used int the detection and tracking of people. Every frame is registered with a reference frame to compensate the object's coordinates. Then the objects that are present in each frame is segmented through k-means clustering and morphological operations. Removal of falsely detected objects is done by the help of their size and shape, Interacting multiple model (IMM) filter is used to continuously estimate the target states. The track is measured using the nearest neighbour association rule. Contour-based background-subtraction is used to extract foreground objects. For pedestrian detection, local adaptive thresholding technique. YOLO helped detecting humans and animals in difficult weather conditions. Particle filter was adopted to track people from aerial thermal view. Further, the Kalman filter with multi-level segmentation tracked people in thermal images. Different targets in a thermal image were tracked using weighted correlation filter. The image characteristics seem to vary depending on the surrounding objects and the climatic conditions, the model proposed shows extensive performance in all the cases. False tracks in this method are reduced from 10 to 1 in the given sample.

Kshitij Agrawal [7]: Ren et al's faster-RCNN implementation is used to train the model for the three datasets acquired - FLIR thermal (FLIR THM), IDD and KITTI. The Faster-RCNN model uses a Resnet-101 for the high-level feature extraction and therefore the complete model is initialized from pre-trained COCO weights. In the initial part of the study, night time images from the FLIR RGB dataset were tested. We inferred that the given dataset does not translate well in thermal domain (night time) in the same dataset. The training on IDD had highest performance and it correlated to the road scenes both in day and night conditions. Testing IDD and KITTI on the FLIR thermal image was unsuccessful which lead to the conclusion that a model that is trained in a visible domain does not respond well in another domain because of the inherent difference in the visual representations.

Jia-Wei Lin [8]: In this paper, thermal cameras are used to visualise body temperature as an image and measure the temperature at different points over a particular area. FLIR lepton 2.5 with breakout board is used to acquire the thermal image. This image is analysed by using ROI in the facial part and then the surface temperature is extracted from the ROI, finally passed through the standardised formula to obtain the result. Single-Shot -Mutlibox Detector with Mobilenet-SSD Architecture is used for the model. All the methods are built on NVIDIA Jetson TX2 and is written using C++ and OpenCV Library. Mean absolute error and root-mean-squared-error metrics are used to express the difference between the verified device and the proposed framework.

B. Miethig [9]: Different thermal signatures of objects in different conditions offer valuable information about a vehicle's environment. With some detection consideration we can use thermal imaging algorithms to detect vehicles and objects. A set of labelled thermal driving data along with an explanation for each class labels including various different driving and weather conditions including misty, snowy, overcast and night time driving. A few dog breeds are also captured which are not readily available in any other open-source mediums.

T. Sonnenberg [10]: In this study, foreign object detection (FOD) and Live object protection (LOP), both required for safe operation of commercial wireless charging electronic vehicle stations, is combined to form a thermal imaging based FOD-LOP system that uses a single sensing device is proposed. Different test models for different models provides successful hardware tests validating the proposed system. The results provide practicality of using this system for high powered WPT models including the charging applications for the vehicle with varying electrical and mechanical parameters and their also widespread adoption.

Kim, J [11]: In this paper, a smartphone based thermal camera is used to detect pedestrians in low light environment and measure the distance from the camera. The camera detects people and calculates all the parameters from the two-dimensional thermal image obtained and use them for further calculations. A USB type infrared camera is attached to the phone and it captures images in different angles in advance. FLIR one pro is used as the thermal camera attached to the device and the experiments are conducted using MATLAB software. The real-world 3D calculations are derived from the acquired 2D thermal images. The results show about 91% accuracy in pedestrian detection and 95% accuracy in measuring the distance.

Naik, K [12]: This study thermal images are used for 3D model generation and in designing algorithms for indoor activity recognition in IoT setup. Initially, the object is identified either as a heat sink or as a heat source and information about the object is generated. Using various algorithms on the obtained data for the activity state. In the next phase, a 3D model is generated from the images obtained from FLIR one pro camera and the RGB stereo. 3D mesh and MeshLab are created using Python APIs of the meta shape tool and are processed in an IoT setup to successfully perform activity recognition. The accuracy of the algorithm is about 93.87%. The HAR's precision, micro recall and F1-score are measured as 78.08%, 95.24%, 0.86 respectively.

Ligocki, A [13]: This study uses RGB camera, thermal camera and 3D LIDAR, and neural networks that are pre-trained in the RGB category. This system allows to train various deep learning models with similar performances as the usual human annotation based models. This RGB annotated images and its object detection phenomena is harnessed into IR image processing methods. FLIR ADAS dataset are used and YOLOv5 framework configures the desired neural networks. Dataset of about 300000 annotated images have been created and tested. The results infer that models that are trained on larger datasets by this method gave better object detection results compared to other models trained on smaller and available hand-annotated data.

Ulhaq, A [14]: This paper proposes a distant object detection algorithm called Distant YOLO that is an upgrade in the traditional YOLO with improved training and structure for auto-detection of targets using thermal imaging. This in turn allows animal detection from higher altitudes that are more accurate and is speeding deep-learning based object detection algorithms. This paper aimed to develop a robust model for the identification of long distant objects, particularly animals. It is not yet clear if D-YOLO is much better than manual detection but the experiment detected all the animals using this algorithm.

Zhao, X [15]: This study proposes a three-dimensional thermography based model to evaluate and analyse the spatial distribution. UAVs are used to capture city models and an IR camera for thermal images to visualise and output thermal temperatures for a specific point. Then, the mean radiant temperatures (MRT) were obtained that provided the space between the sunlit and shaded areas, points were vegetation is lower and the ratio of height to width. These measurements can be used to evaluate the thermal environment. The process includes acquisition of 3D models, 2D thermal images, 3D thermography processing and finally, estimation of Mean Radiant Temperature. The study concluded that the best strategy to create a comfortable pedestrian space is to shade the space as much as we possibly can.

Batchuluun [16]: This paper addresses a method to detect thermal image reflections based on deep learning neural network algorithm (CNN) and eradicating them while post-processing. The experiments are carried out using Dongguk thermal image database (self-collected), DI&V-DB and also an open database showed this method is much more effective than other state-of-the-art methods in this field. Mask R-CNN is used to find the thermal reflections in an image, and these findings are removed in post-processing by morphological dilation and complement operation. The process is implemented using python based Keras API with Tensorflow backend and OpenCV library. The results gathered proved that this proposed methodology showed greater accuracy for image acquisition, detection and removal in comparison to other well recognised methods.

Annapareddy, N [17]: In this paper, thermal imaging is used to detect pedestrian and cyclists using deep learning neural network architecture. This method is evaluated in accordance with the KAIST pedestrian benchmark multispectral dataset with both RGB and thermal images. Thermal images can provide images in high contrast even in low-light environment and extreme climatic conditions. These thermal images are fed to machine learning algorithms and a Faster R-CNN model consisting of both CNN and RPN. The outcome achieved an accuracy of 65.16% and a F1-score of 81.34% with minimum false negatives of about 0.53%. These findings prove to be a baseline to build in multi spectral detection methods.

Mittal, U [18]: This study provides a comparative analysis on application of Faster region based convolutional neural networks and the visual spectrum images. The acquired thermal images are implemented using python and Tensorflow API and was executed on NVIDIA GPU. The experimented results prove that that accuracy of thermal images is superior than the visible spectrum images during night and the accuracy in daylight is almost same for both the type of images. Thermal cameras were comparatively less effective during the day time because of the excessive heat patterns but nonetheless they were accurate. Overall thermal images if effective for all seasons, climate and time are considered as whole. It concludes that thermal images can be used over normal images in various deep learning techniques such as YOLO, Mask R-CNN, SSD etc.

YanpengCao [19] We propose a hybrid method that combines the benefits of model-based ray casting and frame-based image warping to generate high-quality projected images with complete view coverage and abundant thermal details for visualizing the invisible thermal information on 3D objects. The effectiveness of the proposed method has been validated for two typical thermal imaging applications including human body temperature monitoring and non-destructive evaluation of composite materials.

Jiahong dong [20] Daytime driving primarily uses daylight cameras, but autonomous driving using such a setup is compromised in the dark, and consequently, resulting in accidents. The hypothesis is that adding an infrared camera to the existing ADAS will boost the detection rate and accuracy, and further enhance the overall safety. This thesis investigates how well a standalone infrared camera performs onboard vehicle perception tasks such as object detection and classification using both machine learning and deep learning algorithms

Francesco Bongini [21] In this work we propose to simplify the creation of training data adding only a subset of objects of interest to a real scene, thus reducing the cost of modelling a whole environment. In order to improve the quality and visual likelihood of the objects we use a GAN, to further adapt the appearance of the 3D models and to better simulate the output of the shaders used in the 3D animation engine.

Ali Haider [22] A fully convolutional regression network is designed to map the human heat signature in the input thermal image to the spatial density maps. The regressed density map is then post-processed for human detection and localization in the image. The proposed regression-based method can detect humans with 99.16% precision and 98.69% recall, outperforming the state-of-the-art conventional hand-crafted and CNN-based techniques for human detection from thermal images.

Rohan Ippalapally [23] Thermal imaging can be used to classify objects under low-light and dark conditions. We present an extensive study of the models based on the COCO evaluation metrics and other important loss metrics. Experimental results on the FLIR dataset confirm that we can use the pre-trained models in object detection to train, identify, and label objects in thermal images.

Marina Ivasic [24] To evaluate the detection performance, we introduce an original dataset of thermal videos and images that simulate illegal movements around the border and in protected areas and are designed for training machines and deep learning models. The videos are recorded in areas around the forest, in different weather conditions at night– in the clear weather, in the rain, and in the fog, and with people in different body positions (upright, hunched) and movement speeds (regular walking, running) at different ranges from the camera. In addition to using standard camera lenses, telephoto lenses were also used to test their impact on the quality of thermal images and person detection given different weather conditions and distance from the camera.

V Teju[25] Introduced an efficient method of object-detection using the OFSA algorithm._Nonlinear image transfer functions were introduced, and the parameters associated with those functions are determined by image statistics for making adaptive algorithms. To get a transformation matrix for the registration, the landmarks in the images are first detected and a subset of those landmarks were selected to obtain the matrix, we propose a hybrid algorithm for detection, tracking and classification using OFSA algorithm to fuse the registered thermal and visual images.

M. NARENDRAN [26] Detecting dim small targets in infrared images and videos is the main concern of this paper. In the starting Retinex filtering to remove the noise and improve the image quality [1]. Then in the second step, object in infrared image is detected through the support vector machine classifier from the background The segmentation of moving objects in corresponding video frames involves 'Background Subtraction' method [2]. Visible and Thermal images are combined as group of Gaussians for background subtraction, and then blob analysis and fusion rule is applied.

Jih-Gau Juang [27] This study applies thermal sensor fusion of an UAV for path planning, obstacle avoidance, and image processing for outdoor patrol. An UAV can follow a predefined path and search human target by thermal camera. Once the target is found, the UAV hovers above the object. Simultaneously, the location will be sent back to the control center.

V. V. Kniaza [28] We use the IoU and mAP metrics for the object detection task. We use the cumulative matching characteristic (CMC) curves and normalized area-under-curve (nAUC) for the ReID task. The evaluation demonstrated encouraging results and proved that our ThermalReID framework outperforms existing baselines in the ReID accuracy. Furthermore, we demonstrated that the fusion of the semantic data with the input thermal gallery image increases the object detection and localization scores.

Ganbayar Batchuluun[29] Thermal imaging is widely used for image analysing and processing. Some of the various proposed methods are SRR and de-blurring. SRR converts low resolution image into high resolution. Both the methods are done separately. We generated a 3-channel thermal image from an original 1-channel thermal image to obtain more information from a thermal image to increase the performance of the image restoration and the object detection methods

Qiang Zhang[30] A novel end-to-end network for multi-modal salient object detection is proposed which turns the challenge of RGB-T saliency detection to a CNN feature fusion problem. A backbone network (e.g., VGG-16) is first adopted to extract the coarse features from each RGB or thermal infrared image individually, and then several adjacent-depth feature combination (ADFC) modules are designed to extract multi-level refined features for each single-modal input image, considering that features captured at different depths differ in semantic information and visual details

Aparna Akula [31] Thermal infrared images pose challenges of low contrast and lack of sharp edges or boundaries typically required for identifying key points using traditional feature detectors. We address this challenge by designing a local feature detector suitable for infrared images. The proposed WignerMSER features are obtained by transforming the image from the spatial domain to joint space-spatial-frequency domain using pseudo Wigner-Ville Distribution, and thereafter detecting MSERs in the Wigner transformed space.

Mohd Asyraf Zulkifley[32] A Siamese CNN network can be implemented to complement the fully CNN, as it allows a set of recent object templates to be used for matching purposes. Since, Siamese network alone is not accurate especially in the case of occlusions, as the stored templates rarely produce robust matching, we propose a two-stream CNN tracker that combines the fully CNN and the Siamese CNN such that each network keeps a set of matching models to cater to diverse appearance changes.

Niki Trigoni[33] A multiple-model FCNN is proposed, in which a small set of fully connected layers is updated on the top of pre-trained convolutional neural networks. The best sample is selected according to a combined score of appearance similarity, predicted location, and model reliability. The small set of appearance models is updated by using positive and negative training samples, accumulated from two periods of time which are the recent and parent node intervals.

Bushra Khalid **[34]** We are proposing a novel method by combining previously used techniques. We are proposing a model which takes multi-spectral images, fuses them together, drops the useless images and then provides semantic segmentation for each object (person) present in the image. In our proposed methodology we are using CNN for fusion of Visible and thermal images and Deep Learning architectures for classification and localization.

Manish Bhattarai and Manel Martinez-Ramon **[35]:** The main purpose of these journal is to create an automated system that is to capable of real -time intelligent object detection recognition and facilities the improved situation awareness of fire fighters during an emergency response. These makes more informed inferences about the circumstance for their safe navigation through such hazardous and potentially catastrophic pic. CNN have demonstrated outstanding performance in object detection RBG imagery. Q-learning, reinforce learning techniques that assist in path planning and can be vocalized through NLP system. These three components are the backbone of the reach presented here. These are very full for guiding firefighters to safety in difficult condition.

Jun Yang, Wei Wang, Guanng Lin, (Member, IEEE), Ye Qing Sun, &Vixuan Sun **[36]:** In these study we are wanted to overcome the limitation of nature of photographic image due to the internal feature of objects cannot be discovered. So, solve these problem of vision base method, this project gives approach for detecting cracks in infrared thermal imaging steel sheet using convolutional Neural Network (CNN). Also gives information about the computer vision algorithms into traditional non-destructive testing, which provides a more intelligent efficient and accurate method for steel plate crack detection. This works gives accuracy and mean average and mean average precision are 95.54% and 92.41% respectively. Output of original algorithm is increased by 3.18% and 1.88%.

Prashanth Kanadguli **[37]**: In this study, we concentrate in human detection using FCOS based approach. Human data model was created by stochastic deep learning. By mean average precision(mAP) indicates that modelling using FCOS performs in promising way object detection and classification algorithms established on convolutional networks. The implementation of Human detection exists in two ways. The classic option uses HOS+SVM which works pleasantly on MTT data set. An improved DPM algorithm has strong robustness to deformation of the human and component-based detection method. For these the precision and recall are 0.91 to 0.97 and 0.86 to 0.94 respectively.

Marco Costanzo, Giuseppe De Maria, Gaetano Lettera, Ciro Natale &Dario Perrone **[38]**: This Journal says importance of human detection to avoid unnecessary robot stops (or) slowdowns in case of false positives. This also says about HRC problem by introducing a novel approach to robustly detect human operator in collaborative work cell through a multimodal perception system aimed at minimizing false positive to avoid unnecessary robot shop. These also gives guarantees human safety in general multi-robot scenarios. To detect human operator in general multi-robot, a multi-model perception system based on a thermal and a depth camera adopted. CNN trained to detect human in workspace.

Farzeen M unir, Shoaib Azam, Muhamnd Aasim Rafique, Ahmad Mugeem Sheri, Moongu Jean, Witoed Pedrycz **[39]**: This work gives a domain adaptation frame work which works a style transfer technique for transfer learning from visible spectrum image to thermal image. A multi-style transfer approach works for the translation of low-level features such as curvatures and edges from the sources domain to target domain .By the use of deep learning -based object detection architecture the rely on classical backbone like VGG, ResNet are trained on the multistyle transfer image from scratch for the robust objection detection in the thermal domain(target Domain).The HOG features and LBP are used to extract features such as mean and contrast to compute a set of features that are then used to train the SUM classifier .Also utilizes MSG Net to transfer low-level sematic feature in act .The outperforms in act. The outperforms the existing bench mark for object.

Weikang Si, Li bing Zheng, Shuhua Wei **[40]**: This work says about importance of thermal reflectance imaging to determine the thermal distribution and heat propagating semi conduction deceives. The Thermoreflectance coefficient(cth) depends on the wavelength and material, so calibration for specific wavelength and material is essential to get accurate temperature. These thermoreflection imaging measurement and two dimensional measurement based CCD.Using Fourier transform and boxer average thermal imaging at microsecond time resolution has been achieved. All these makes a result which says response time of metal heating is much faster than that of substrate silicon.

Romenick D, poster, Shuwen Hu, Nathanj, short, Benjamin, s, Riggen and Nasser M. Nasrabad [41]: These journal is to assess the potential of visible to thermal transfer learning for thermal face landmark detection. In this used investigate the use of parameter transfer learning for enhancing thermal face landmark detection by level ageing visible face data during training he transfer learning techniques: LLR, LKR, RPT, AAM.As such, these methods are well suited to mutispected data sets which lack precisely aligned and time synchronized.

Dong Zhang, Zhonyi Guo [42]: The work says the development of laboratory patrol to a certain extent guarantee the safety of experiment teaching to all. The aim is to design a sentry robot, which could take appropriate emergency measures to detect dangerous situation, including alarms and care out firefighting to minimize the accident and loss of economy. This also carry out an applied research on the combination of artificial intelligence and laboratory safety management for pharmaceutical professional laboratories.

Monhamed Yahia, Rahul Gawai,Tarig Ali,MD Marufmortula Lu Tfi Albasha,& Taha Landolsi [43]:This paper is to detect the water linkage by multi temporal Infrared thermogragh.IR image is found to find the temporal temperature variation due to water leakage and mitigate the field temperature effect.CV is image which is noise less. TVI histogram threshold was defined to classify the TVI image into leakage. The closed-circuit Television(CCTV) is well known technique the leakage detection WDN setup , the soil temperature variation was determined. Result came like the classical spatial analysis can detect water leakage areas but false positive can be observed.

Yangyang Lian, Zhihui Wang, Hanqing Yuan, Lifang Gao, Zhuozhi Yu, Wenwei Chen, Yifei Xing, Siya Xu, Lei Feng [44]:This work, says about face recognition is an important means of security authentication. The face features obtained by principal component analysis (PCA) algorithm. Also, the accuracy of face recognition is mainly affected by factor such as lighting, motion and occlusion combining infrared thermal imaging to locate acupoints with the traditional with the traditional face recognition method, it improves uses experience. These algorithm trains lots of face image and no face image and no face recognition method based on infrared thermal imp ageing assistance proposed in this paper can improves the accuracy of face recognition is higher 50%.

Pialutzen [45]: In these work, a thermal image processing algorithm is presented which intends the sensor to be mounted on a moving device or vehicle. The algorithm is conceived for object covering a sensor area between 0.3%-1.5%. This realized by means pf computer vision by library “OpenCV”. This includes steps like convert image to grayscale, divide image in block image in block, background subtraction investigates mean in intensity of each block contour area, Detection success. Depend on the target size the algorithms parameters of block size, mean intensity and area limits have to be adapted to ensure a reliable operation.

Hannah Bergenroth [46]: The journal, gives the evaluation of the proposed moving detection system and the information of multiple sensor these could create a system that can work for round-the clock monitoring. Applying DCNN for image classification, deep learning method have become state-of-the-art-in image recognition and made considerable improvement in areas. In computer neural network is to emulate what human do well and then scale it up to take advantage of the speed of modern computer. Single-stage detector such YOLO and single shot multi box detector (SSD) used for region proposal stage.

Frederik s,lea,Hakon Hagesen,Tol Arne Johansen,Thor,I,Johansen[47]: In these work, the data average object infrared radiation will be somewhat dependent on the UASs distance and attitude relative to the object hence if the UAU altitude was to change drastically the reference for the object detected average infrared radiation should be adjusted the object detection , recognition and tracking algorithm was tested in four different UAU flight different UAU flight rest conducted over sea from the shoreside just outside trophism.

Ravi Yadav, Ahmed Samir, Hazem Rashe, Senthil Yogamani and Rozenn Dahyot [48]: This work is to provide a high information density at a low cost. Color model outperforms thermal in a day condition and thermal models outperforms color in night condition illustrating their complementary nature. These in construction of CNN based fusion architecture and unimodal baselines A baseline study of the three network for day and night time scenes separately. Experimentation on two automotive dataset namely KAIST and FLIR state of the art results on KAIST. These demonstrated that a simple end to end CNN architecture is able for data resolution.

QiangYao ,ShunchaoQi, HaoyangLi, XingguoYang, HongtaoLi[49]: This journals is on the collected infrared image, multiple image, multiple image enhancement and segmentation algorithm were comparatively analysed. These also explores the depth how to perform image identification for the rock grain gradation using infrared thermography and proposed and infrared image -based identification method for rock grain gradiation using heating. This journal also uses an infrared video camera to perform image sampling heated rock grain, According to maximum stability theory, the shortest side of the minimum enclosing rectangle (MER) of grain image is prosed as the judgment index for grain, respectively.

Marcin Kowalski [50] These work says about Thermal infrared imaging offers specific physical properties that may boost presentation attack detection capabilities. These also say about is to present outcomes of investigations on the detection of various face presentation attacks in thermal infrared in various conditions including thermal heating of masks and various states of subjects. Meanwhile the spoofing masks were spectrally characterized. Collected data including attacks composed of the thermal face spoofing dataset (TFSD) that is published along with this manuscript.

Literature Survey:

S.no	paper	Image acquisition	Image enhancement	Image segmentation	Image restoration	Feature extraction	Classifier	Metrics	Remark
1.	Muhammad Sheikh Sadi	MS COCO set	Horizontal and vertical flipping, mirroring, zooming	Thresholding	Pi camera module V2+prototype	Mobile Net	SSD	Accuracy-99.31% in object detection and recognition is 98.43	The IoT based automated system is able to recognise objects both in indoor and outdoor environment. Thus, mobility issues can be aided for visually challenged people.
2.	Kalita, R	KAIST bench mark data set	Faster RCNN			Dark Net19, HOG, ACF, ICF	YOLOv3	Average precision-95.5%, miss rate-4.7	. YOLO detector for thermal images when trained with COCO dataset are not much efficient compared to the usual algorithms since thermal images differ from the usual RGB images.

3.	Aparna	Thermal image dataset	Average pooling, resizing, cropping	Radiology, CNN	Morphology filter histogram		CNN, ANN, SSVM	Accuracy-97.08% & average validation accuracy-70.62%	Thermal images prove to be very efficient in detection of potholes at any condition over other techniques.
4.	Debasmita Ghose	KAIST Multispectral dataset	Faster RCNN	SDS R-CNN	Amulet integrates	Deep learning techniques	PICA-Net, R^3Net, R-CNN		. Deep saliency networks that are trained on KAIST dataset can be used to extract saliency maps from the given thermal images. This information provided to pedestrian detector shows to be more efficient than the baseline approach.
5.	Ophoff	Image Net Dataset					Single pass CNN, YOLO, SSD		On an average, mid to late RGB+Depth fusion level with single-pass detection networks increases accuracy and localization regardless of

									the depth acquisition method.
6.	Yeom, S	FLIR Dataset	Contour-based background subtraction	k-means clustering	Interacting multiple model filter (IMM)	Supplementary material video	TR thermal camera		This detection and tracking method are proven to be useful for surveillance, smart security and search and rescue missions over hazardous areas even in adverse conditions.
7.	Kshitij Agrawal	FLIR ADAS dataset	Faster RCNN			Resnet, deep learning	SVM	mAP-68% accuracy-89%	This detection and tracking method are proven to be useful for surveillance, smart security and search and rescue missions over hazardous areas even in adverse conditions.

8.	Jia-Wei Lin	FLIR dataset	Ostu's method		Machine learning based method, filter (KCF) tracker		CBTM		With a low-cost LWIR camera a CBTM system is developed and new model based on deep-learning techniques with tracking algorithms applied to track face. Temperature is obtained from the calibrated formula.
9.	B. Miethig	Thermal image dataset	IR cameras		LIDAR	Approximated object dimension &relative			New set of labelled thermal data and explanation for each class is provided for all conditions. Additionally thermal image dataset for two dog breeds that aren't readily available is given.

10.	T. Sonnenberg	Training and testing set	Fkipping, threshold		FLIR lepton module	Triggering image	CNN		FOD-LOP for WPT applications is proposed using thermal images. WPT systems are practical and safe thereby can be adopted in various domains.
11.	Kim, J	FLIR dataset	USB type infrared camera		CCD vision camera	Multilevel restored learning, thermal image	HOG	Accuracy-95%	Thermal imaging based pedestrian detector that is efficient for low-light conditions and the estimated distance is also found.
12.	Naik, K	FLIR dataset, COCO data set	histogram	Flow-based segmentation		Gain energy image, pca, mda, machine learning	CNN	Accuracy-93.87, precision-78.08%, recall-95.25%	Different optical imagery and thermal imaging based algorithm for activity recognition and 3D thermal model generator for indoor environment is successfully proposed. This method can be

									used in various domains readily.
13.	Ligocki, A	Lage scale thermal image-dataset	Homogenous transformation	YOLOv5 feature used by cropping			Transfer learning techniques, CNN	Map-63.4%to 78.6mAP	. RGB and thermal cameras combined with LiDAR sensor is used for the automatic annotation of thermal images. Models trained on large scale dataset gave better thermal image detection than significantly smaller annotated data.
14.	Ulhaq, A	Thermal image data set	Histogram equalization	k-means clustering	Gaussian filter		SVM	Accuracy-87.876 Precision-78.9%	Validates the robust detection to identify animals from aerial view. D-YOLO is used for remote

									detection of small objects.
15.	Zhao, X	FLIP data set	Wavelet transform	Patch based segmentation	Multiple filters		CNN, SVM	Accuracy-90.90%	. MRT at different heights in the sunlit regions is much larger than in the shaded regions with maximum difference of 1.6 °C.
16,	Batchuluun	Image data set	Constant stretching	Image subtraction	Weiner filter		Fourier transformation	Recall-90.89% Accuracy-98.09%	. MRT at different heights in the sunlit regions is much larger than in the shaded regions with maximum difference of 1.6 °C.

17.	Annapareddy, N	FLIR dataset	Pixel subtraction	Morphological operation	Kernel filter		CNN	Precision-99.87%	Minimum false negatives and higher F1 score implies that this robust method to identify cyclists and pedestrians using thermal images is accurate and effective.
18.	Mittal, U	Image data set	threshold	Median filter	PCA		SoftMax	Accuracy-90.99%	. Thermal images at low illumination conditions show better quality and the thermal images captured in daylight due to the excessive heat but the overall efficacy is undeterred.
19	Yanpeng Cao	FLIR dataset	Histogram equalization	_	Threshold based maximum entropy	PCA	SVM	Accuracy>90%	Properties of thermal imaging is used to determine properties of 3D objects
20	JIAHONG DONG	Custom made dataset	Histogram equalization	_	Deep learning	SVM	YOLOv4	Avg. precision>50% Avg. recall>60%	This thesis has explored the background of autonomous

									driving, the current trend of autonomous driving, sensors and their capabilities, image processing techniques, camera calibration methods, and machine learning and deep learning-based detection and classification algorithms
21	Francesco Bongini	FLIR dataset	GAN	deblurring	RCNN		CNN	Precision-76.37%	In this paper we compared several data augmentation strategies to improve a YOLOv3 detector working in a thermal-only domain.
22	AliHaider	Fig share dataset	Histogram equalization	Direct inverse filtering	_	_	CNN	Precision-99.16% Recall-98.69%	the detection performance is on par with the state-of-the-art fully convolutional architectures

									for predicting the density maps for human detection in thermal images
23	Rohan Ippalapally	FLIR dataset	De-blurring	deconvolution	K-means algorithm	GLCM	SVM	_	Detects and classifies objects under low-light and dark conditions
24	Marina Ivasic-Kos	Original dataset of thermal images	Manual annotation	_	Grayscale conversion	R-CNN		Precision-100% Recall-15.5%	Detects and differentiates objects in extreme weather conditions
25	V Teju	Kaggle	Median filtering	Morphological operations	Threshold based maximum entropy	PCA	SoftMax	High accuracy	we propose a hybrid algorithm for detection, tracking and classification using OFSA algorithm to fuse the registered thermal and visual images.
26	M. NARENDRAN	FLIR	Convolution Neural Networks	Retinex filtering	Background Subtraction	Image fusion	SVM	Accuracy-98.42%	Aim is to build a system that acquires an image from image recognition and detects target object

27	Jih-Gau Juang	FLIR dataset	Contrast stretching	_	_	Deep learning	YOLO	High accuracy	Detects and traces the object using deep learning and YOLOV3
28	V. V. Kniaza	LAERT	_	deconvolution	robust segmentation technique	CNN	_	Poor accuracy	We developed the ThermalReID framework for cross-modality object re-identification
29	Ganbayar Batchuluun	Thermal dataset	SRR	deblurring	FCN	_	_	High accuracy	Detects and deblurs images and increases processing speed
30	Qiang Zhang	RGB dataset	Histogram equalization	_	Threshold based segmentation	Deep learning	RCNN	_	Detects objects especially under challenging conditions, such as poor illumination, complex background and low contrast
31	Aparna Akula	FLIR dataset	Spatial domain	deblurring	_	MSER	_	5% increase in accuracy	WignerMSER, a robust local feature detector for thermal infrared images is introduced
32	Mohd Asyraf Zulkifley	Training dataset	CNN	Size smoothing	_	_	RCNN	Moderate accuracy	the two-stream CNN

								Failure rate-1.76	tracker has managed to integrate both full CNN and Siamese CNN streams to improve tracking accuracy
33	Niki Trigoni	FLIR dataset	FCNN	deblurring	k-means algorithm	Deep learning	_	Avg. accuracy>0.1	MMFCNN works the best in the situation of blur image caused by abrupt movement changes
34	Bushra Khalid	KAIST	CNN	Deep learning	Pixel segmentation	convolution	HOG	Miss rate - 43.80%	The purpose of this paper is to utilize modern technology and computer vision models for efficient surveillance and the provision of fool proof security in organizations
35.	Manish Bahattarai	Training and test dataset	RELU activation, software activation	Threshold based	Micro bolometer vanadium oxide(vox)	NLP system & q-learning	CNN	Accuracy 97 to 99.8%	It gives us understandable videos for taking better protocol. All methods used here are fused

									to accomplish the ultimate goal of providing an artificially intelligent solution capable of guiding fire fighter to safety in worst case scenarios
36.	Jun Yang, Wei Wang, Guanng Lin, (Member, IEEE), Ye Qing Sun, &Vixuan Sun	Thermal data set	FCNN	Deep learning	k-means algorithm	Machine learning	CNN	Avg. accuracy=0.1	It gives information about the computer vision algorithms into traditional non-destructive testing, which provides a more intelligent efficient and accurate method for steel plate crack detection.
37.	Prashanth Kannadaguli	MIT dataset, thermal data set	Histogram matching	Threshold sematic segmentation	Median filter	Stochastic deep learning	CNN	Pecision-0.91 to 0.97, recall-0.86 to 0.94	These is very effective gives promising way and it can be used in automatic human detection system

38.	Marco Costanzo, Giuseppe De Maria, Gaetano Lettera, Ciro Natale &Dario Perrone	MS-COCO dataset	HDT algorithm	Histogram of oriented gradient, subtraction of stored back ground	URDF filter	Machine learning	CNN, YOLOv3	Map D-CNN-65.09 T-CNN-76 DT-CNN-57.54	This is useful for future development well be devoted to devise on SSM strategy where, rather than assuming a constant minimum protective distance, its computed based on the actual robot And human velocities estimated through the same perception data used for distance computation.
39	Farzeen M unir, Shoaib Azam, Muhamnd Aasim Rafique, Ahmad Mugeem Sheri, Moongu Jean, Witoed Pedrycz	FLIR-ADAS dataset	Cross domain model, transfer paradigm	Classical image processing	Faster-RCNN	Histogram of orienteered gradient (HOG), LBP	SVM	Accuracy-89.24% to 98.96% Recall-93.98%	This is very effective and gives away from a challenging condition by using thermal image which becomes effective foe autonomous driving

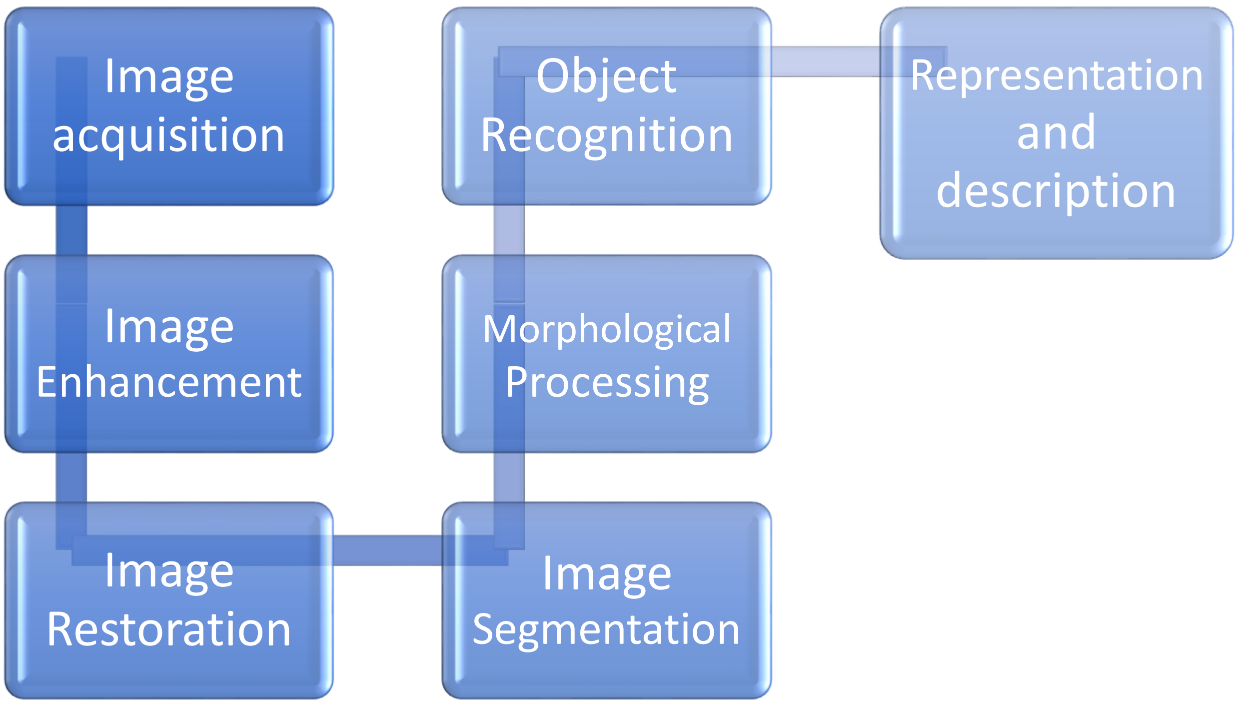
40.	Weikang Si, Li bing Zheng, Shuhua Wei	Thermo reflectance imaging	Pixel's addition	calibration	Optical band filter	Fourier transform & boxer averaging	Thermo reflectance image technology	Accuracy-76.89% Recall-76.90%	This work is full in detecting temperature rise in micro resistance using thermo reflectance imaging is more effective.
41.	Romenick D, poster, Shuwen Hu, Nathanj, short, Benjamin, s, Riggen and Nasser M. Nasrabad	Thermal face dataset	Cumulative error distribution curve + threshold	Horizontal flipping, random translation, scaling	Basler scouts' series cameras, thermal infrared camera	Face landmark, HOG, Transfer learning	SVN	Precision-96.72% to 99.87%, accuracy-99.87	This work is very useful in demonstrating that transfer learning leveraging visible spectrum data improves thermal face landmarking.
42.	Dong Zhang, Zhonyi Guo	RGB dataset	Etching & swelling treatment	RGB colour segmentation + flame motion	Mean filter	Moving region & judging flame colour	SVM	False recognition rate-25% Thermal image reconition-70%	This useful work is assisted laboratory safety patrol in order to reduce the incidence of laboratory safety accidents to minimum
43.	Monhamed Yahia, Rahul Gawai, Tarig Ali, MD Marufmortula Lu Tfi Albasha, &Taha Landolsi	IR dataset	TVI histogram	Pixel addition	IR water leak detection techniques	Water leak detection	CCTV	Acucuracy-56.87	These is very effective in detection of water leakage by infrared thermal. CCTV

									is used detect water leakage
44.	Yang yang Lian, Zhihui Wang, Hanqing Yuan, Lifang Gao, Zhuozhi Yu, Wenwei Chen, Yifei Xing, Siya Xu, Lei Feng	Principal component analysis	SVM kernel	Pixel subtraction	Median filter	K-L transformation	Cascade classifier of harr features, SVM	Face recognition-50%	PCA algorithm used for facial features, determine the occlusion of the face. This is very effective also says the method of intelligent face recognition
45.	Pialutzen	Image Net database	Morphological transformation	Background subtraction base	Multiple filters	Detect the senor area	CNN	Accuracy-79% Precision 56%	This work is important to know importance of the target should cover a significant sensor area. It says that the algorithm is reasonable at a certain. Kind of background
46.	Hannah Bergenroth	Image Net dataset	R-CNN	Background subtraction on gaussian mixture models	Filter + Kernel	Deep learning, transfer learning, machine learning	SoftMax, SVM	Accuracy-92%, precision-0.92% Recall-0.92	This work is useful to detect the moving object by utilizing information from different sensors. Also gives benefits of multiple sensor

47.	Frederik s, lea, Hakon Hagesen, Tol Arne Johansen, Thor, I, Johansen	FLIR dataset	Prewitt operation, kernel approximating a gaussian distribution	Machine vision and module task	Kalman filter	Machine learning	SVM, CNN	Accuracy-90.87%	This work is useful for describing object observation from air are very important as the attitude angle and orientation that the object is viewed from are constantly changing
48.	Ravi Yadav, Ahmed Samir, Hazem Rashe, Senthil Yogamani and Rozenn Dahyot	KAIST dataset, FLIR dataset	Faster R-CNN	Pixel addition	Multiple filter used	Deep leaning	CNN, SVM	Presession-45%	This work gives the simple end CNN end architecture is able to effectively fuse when the input data resolution
49.	QiangYao ,ShunchaoQi, HaoyangLi, XingguoYang, HongtaoLi	Thermal image dataset	calibration	OSTU method	HDT	Transfer learning	CNN	Accuracy-89.09%	This work is very effective analysis One group of riverbed pebbles and one group of blasted gravels And its experiment on sampled grain in each group
50.	Marcin Kowalski	FLIR data set	fasterRCNN	PIXEL subtraction	Multiple filters	Attack detection, deep leaning	SVM	Accuracy 56% to 60%	These work is very good in a study on

									presentation attack detection (PAD) in thermal infrared using simple two-dimensional attacks, as well as novel 3D facial masks

Project Modules:



Module description:

- Image acquisition:

For the image acquisition we used FLIR Thermal dataset. Our Dataset contains over 14,000 thermal images, both synced annotated thermal imagery and non-annotated RGB imagery for reference. The camera centrelines approximately 2 inches apart and collimated to minimize parallax.

https://www.flir.com/oem/adas/adas-dataset-form/

- Image Enhancement:

Image enhancement is the procedure of improving the quality and information content, as well as weakening or removing any unnecessary information according to specific needs of original data before processing. The goal of image enhancement is that the image should be interpretable for human viewers or to provide a better quality input for any further image processing techniques. For our project we choose **Histogram equalization** to enhance the dataset images.

Histogram equalization adjusts the contrast of an image by spreading out most frequent pixel intensity values or stretching the intensity range of the image. It is highly efficient and simple contrast-enhancement technique. It can be used for modifying the dynamic range and contrast of an image by altering it such that its intensity histogram is evenly stretched and has the desired shape. Low contrast images have histograms that are concentrated within a tight range of nearby values. When we use this technique to the low-contrast image, it improves the contrast and quality of the image due to its uniform distribution of intensity values.

- Image Restoration:

Image restoration is performed to undo the defects in a degraded image. Degradation comes in form of motion blur, noise, and camera misfocus.

To improve the signal-to-noise ratio, and thus the clarity of the dataset, we have used inverse fast Fourier transform (ifft). IDFT is the inverse of DFT and can be used to restore images by combining the constituent frequencies. To reduce the mathematical operations used in the calculation of DFT and IDFT, we have used IFFT which corresponds to IDFT.

We start by taking the Fourier transform of the degraded image (blur and noise) and shift it to the centre of spectrum. For every point in the image, we divide the Fourier transform of the degraded by the Fourier transform of degradation function. We finally apply inverse Fourier to restore the image.

- Image Segmentation:

Threshold method is the best and widely used method in image segmentation which divides the pixels in an image by comparing the pixel's intensity with a specified value (threshold). This divides all the pixels of the input image into 2 groups one is pixels having intensity value lower than threshold and then pixels having intensity value greater than threshold. Here we use the Otsu's method to find the threshold level value.

It is useful when the required object has a higher intensity than the background. In thresholding, we can also convert an image from colour or grayscale into a binary image.

Here we can also change the pixels of an image to make the image easier to analyse.

- Morphological Processing:

Morphological processing is a broad set of image processing techniques that process images based on their geometrical structures and shapes based on set theory, lattice theory, topology etc. Images may contain various imperfections such as the distortion by noise and texture after simple thresholding. Morphological processing is used to remove these imperfections and account for the form and structure of the image. For our project we use **Dilation and Erosion** techniques. To an image, dilation adds pixels to the boundaries of objects while erosion removes irrelevant pixels on object boundaries. Dilation expands the image pixels, the value of the output pixel the maximum value of all the pixels in the neighbourhood. Erosion shrinks the image and leads to thinning but it strips away the extrusion.

- Object recognition

Object recognition is a computer vision technique for identifying objects in images or videos. Object recognition is a key output of deep learning and machine learning algorithms.

In order to train our image dataset (FLIR image dataset) we use YOLO V2 Network. We start by loading the training data for vehicle detection into the workspace. We then create an imageDatastore using the files from the table and load the preinitialized YOLO v2 object detection network. We train the YOLO v2 Network and inspect the properties of the detector.

For feature extraction and classification, we use CNN as classifier. We use fasterRCNN on the loaded image and store the locations of the bounding boxes and their detection scores. Finally annotate the image with the detections and their scores.

Project Implementation:

```
clc;
clear all;
close all;
orgimg = imread("FLIR_00922.jpeg");
%Histogram equalization
f = histeq(orgimg);
montage({orgimg, f },"Size",[1 2]);
title("Original Image and Enhanced Images using histeq ");
%DFT Transform
f=imresize(f,[256 256])
figure,(imshow(f))
[M,N]=size(f);
h=fspecial('gaussian',260,2);
g=(imfilter(f,h,'circular'));
figure,imshow(g,[]);
G = fftshift(fft2(g));
figure,imshow(log(abs(G)),[]);
H = fftshift(fft2(h));
figure,imshow(log(abs(H)),[]);
F = zeros(size(f));
R=70;
for u=1:size(f,2)
    for v=1:size(f,1)
        du = u - size(f,2)/2;
        dv = v - size(f,1)/2;
        if du^2 + dv^2 <= R^2;
            F(v,u) = G(v,u)./H(v,u);
        end
    end
end
figure,imshow(log(abs(F)),[]);
fRestored = abs(ifftshift(ifft2(F)));
figure,imshow(fRestored, []), title('restored image');
%Gray level Thresolding
level=graythresh(f);
```

```
c= im2bw(f,level);
subplot(1,2,1), imshow(f),title('original image');
subplot(1,2,2), imshow(c),title('threshold image');
%Morphological processing
subplot(2,2,1), imshow(c),title('original image');
s=strel('line',3,3);
dilated=imdilate(c,s);
subplot(222), imshow(dilated),title('dilated image');
eroded=imerode(c,s);
subplot(223), imshow(eroded),title('eroded image');
figure,imshow(fRestored, []), title('restored image');
%ObjectRecognition
data = load('vehicleTrainingData.mat');
trainingData = data.vehicleTrainingData;
dataDir = fullfile(toolboxdir('vision'),'visiondata');
trainingData.imageFilename = fullfile(dataDir,trainingData.imageFilename);
rng(0);
shuffledIdx = randperm(height(trainingData));
trainingData = trainingData(shuffledIdx,:);
imds = imageDatastore(trainingData.imageFilename);
blds = boxLabelDatastore(trainingData(:,2:end));
ds = combine(imds, blds);
net = load('yolov2VehicleDetector.mat');
detector = net.detector;
results = detect(detector, imds);
[ap, recall, precision] = evaluateDetectionPrecision(results, blds);
figure;
plot(recall, precision);
grid on
title(sprintf('Average precision = %.1f', ap))
lgraph = net.lgraph
lgraph.Layers
options = trainingOptions('sgdm',...
          'InitialLearnRate',0.001,...
          'Verbose',true,...
          'MiniBatchSize',16,...
          'MaxEpochs',30,...
          'Shuffle','never',...
          'VerboseFrequency',30,...
          'CheckpointPath',tempdir);
[detector,info] = trainYOLOv2ObjectDetector(ds,lgraph,options);
detector
figure
plot(info.TrainingLoss)
grid on
xlabel('Number of Iterations')
ylabel('Training Loss for Each Iteration')
fasterRCNN = vehicleDetectorFasterRCNN;
I = imread('FLIR_03447.jpeg');
[bboxes,scores] = detect(fasterRCNN,I);
I = insertObjectAnnotation(I,'rectangle',bboxes,scores);
figure
imshow(I)
title('Detected Vehicles and Detection Scores')

peopleDetector=vision.PeopleDetector;
[bboxes,score]=peopleDetector(I);
if(sum(sum(bboxes))~=0)
    x=insertObjectAnnotation(I,'rectangle',bboxes,score);
    imshow(x);
    title('Detected People and detection scores');
else
    imshow(I);
    title('No People Detected');
end
```

Results:

Result of Histogram equalisation:

1.

Original image:

Enhanced image:

2.

Original image:

Enhanced image:

3.

Original image:

Enhanced image:

4.

Original image:

Enhanced image:

5.

Original image:

Enhanced image:

Result of DFT Transform:

1.

ORIGINAL IMAGE:

Restored Images: FIG.NO:1:

Restored FIG.NO:2:

Restored FIG.NO:3:

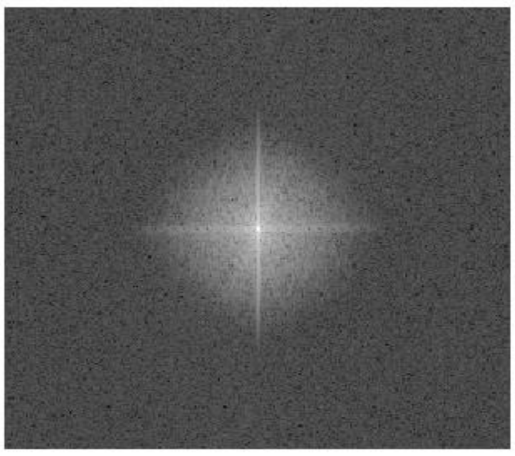
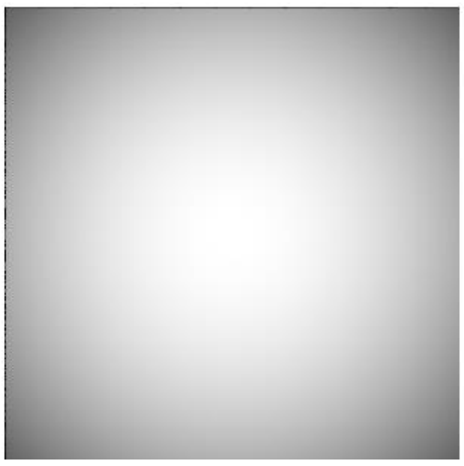
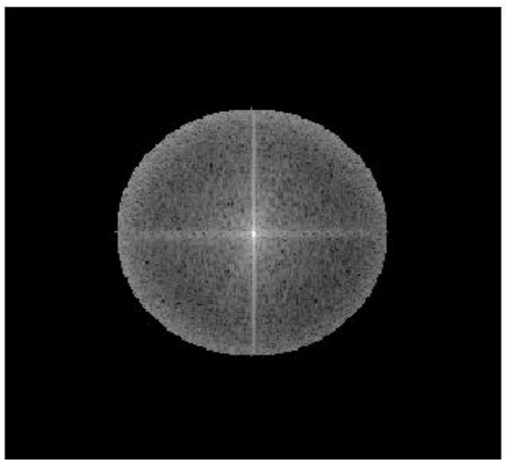


FIG.NO:4:



Restored FIG.NO:5:



Restored IMAGE:

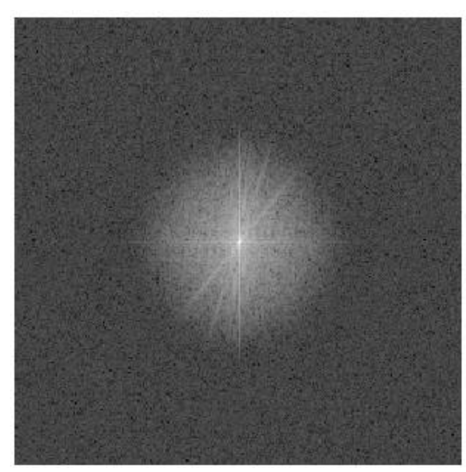
2.

Original image:

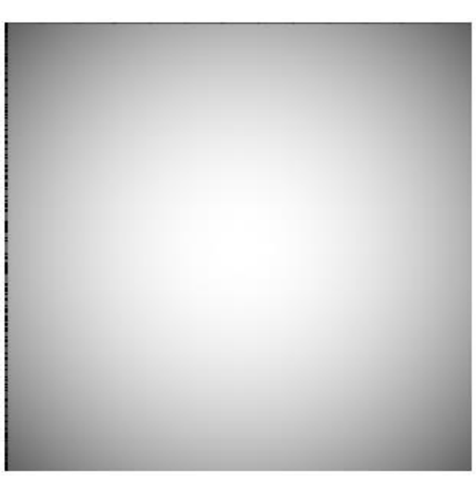
Resorted image FIG.NO:1

Resorted image FIG.NO:2

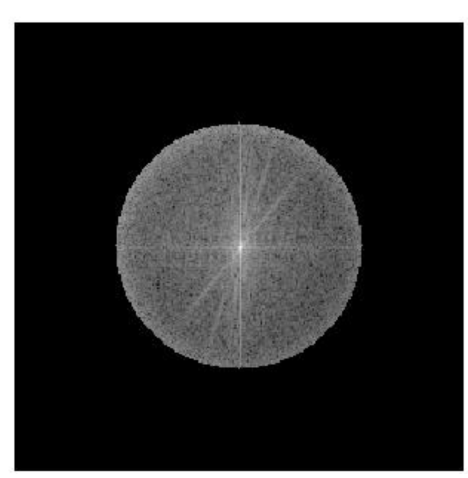
Resorted image FIG.NO:3:



Resorted image FIG.NO:5



Resorted image FIG.NO:6



RESORTED IMAGE:

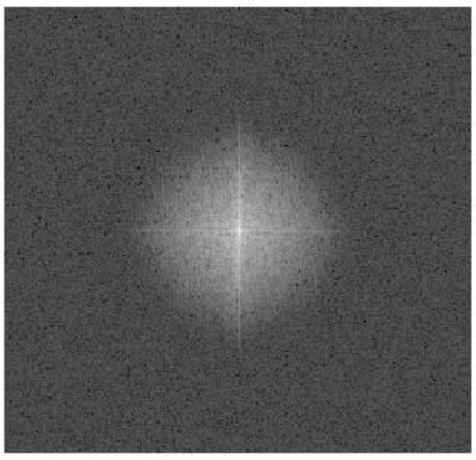
3.

Original image:

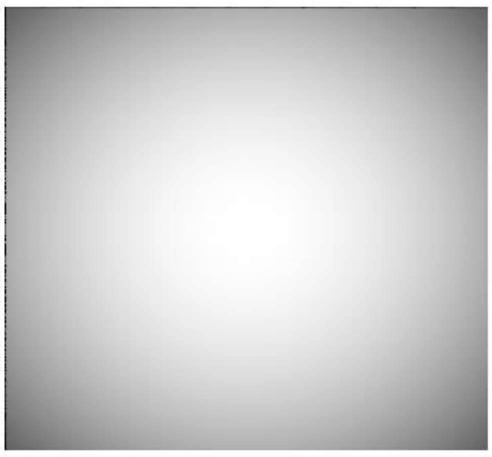
Resorted image: FIG.NO:1

Resorted image: FIG.NO:2:

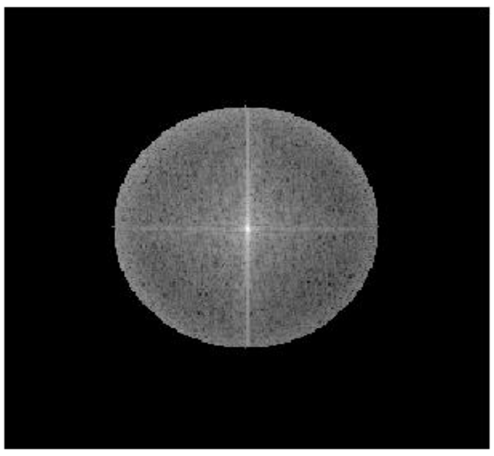
Resorted image: FIG.NO:3:



Resorted image: FIG.NO:4:



Resorted image: FIG.NO:5



Resorted image:

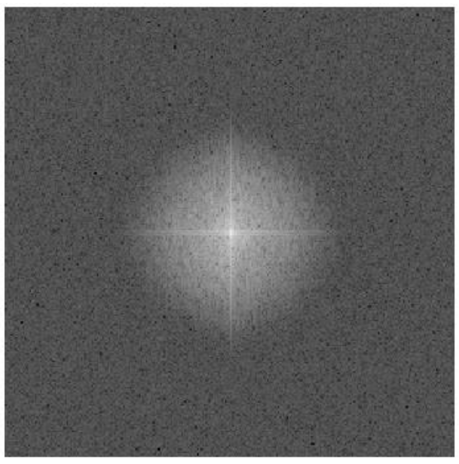
4.

Original image:

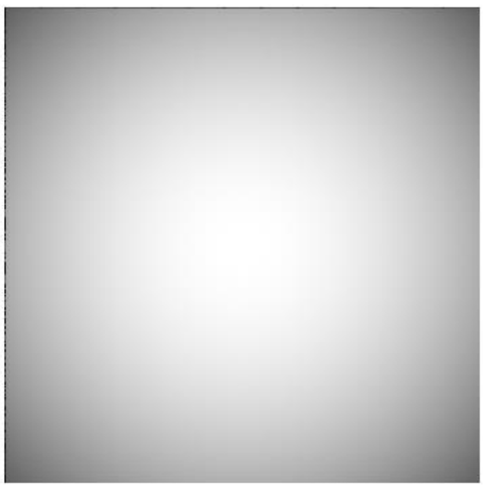
Resorted image: FIG.NO:1:

Resorted image: FIG.NO:2:

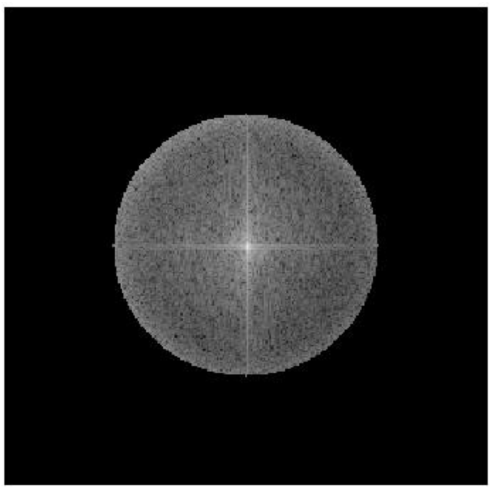
Resorted image: FIG.NO:3:



Resorted image: FIG.NO:4:



Resorted image: FIG.NO:5:



Resorted image:

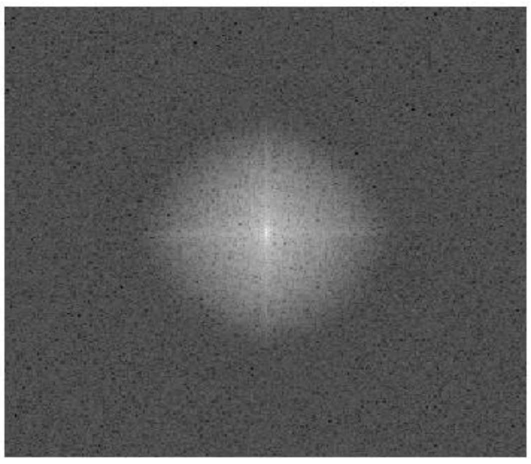
5.

Original image:

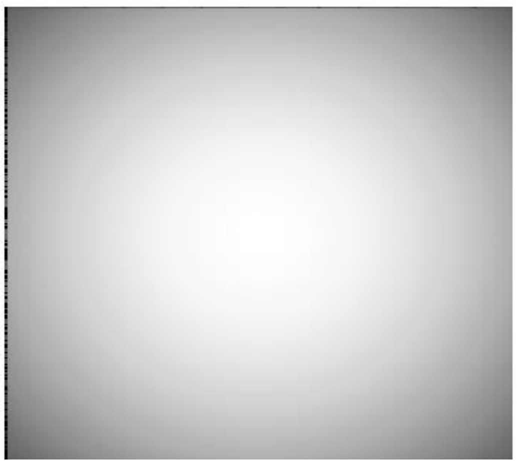
Resorted image: FIG.NO:1:

Resorted image: FIG.NO:2:

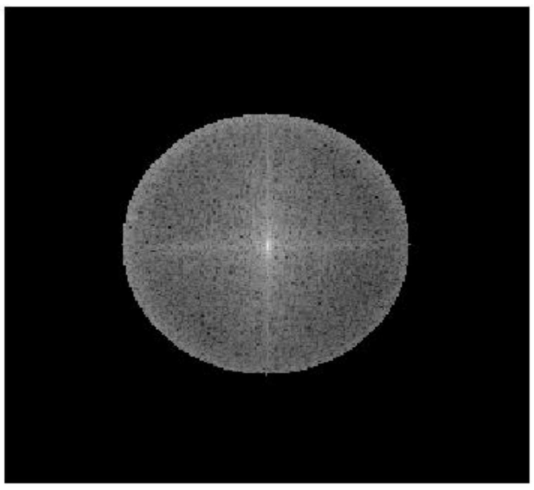
Resorted image: FIG.NO:3



Resorted image: FIG.NO:4:



Resorted image: FIG.NO:5:



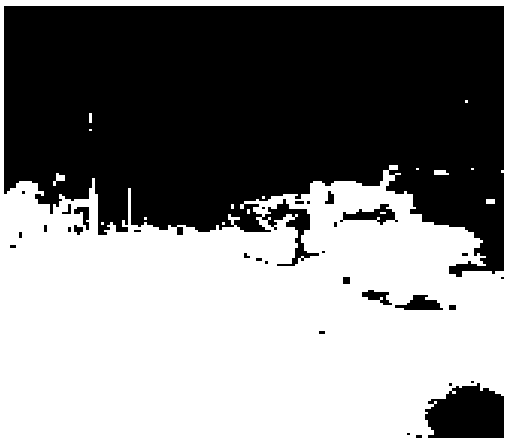
Resorted image:

Result of Gray level Thresholding:

1.

Original image:

Thresholded image:



2.

Original image:

Thresholded image:

3.

Original image:

Thresholded image:

4.

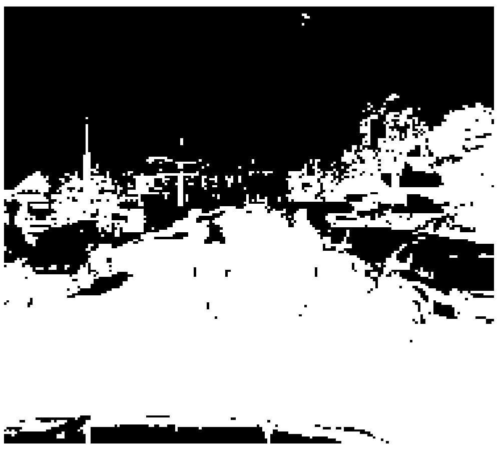
Original image:

Thresholded image:

5.

Original image:

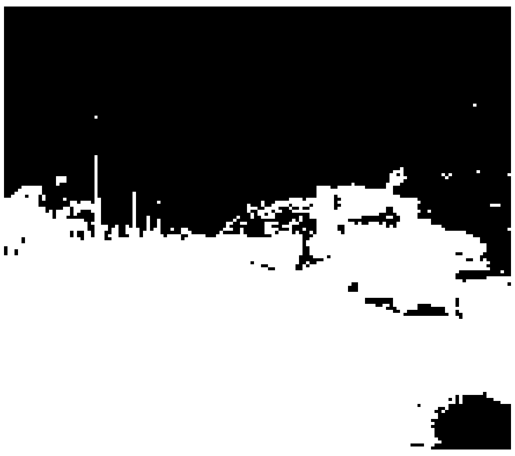
Thresholded image:



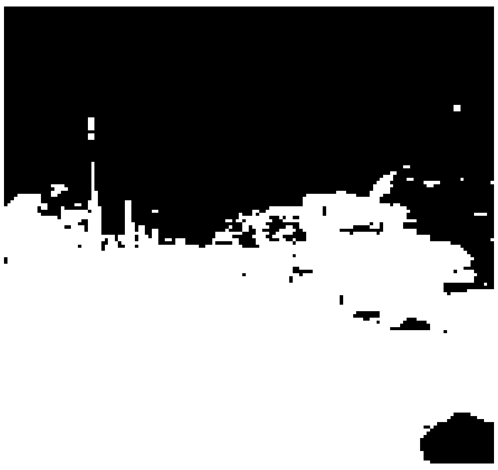
Result of Morphological processing:

1.

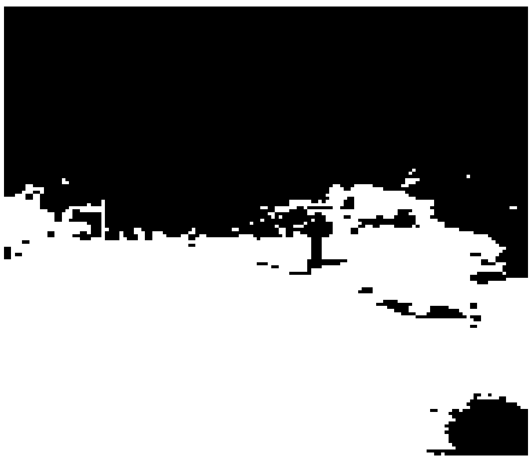
Original image:



Dilated image:



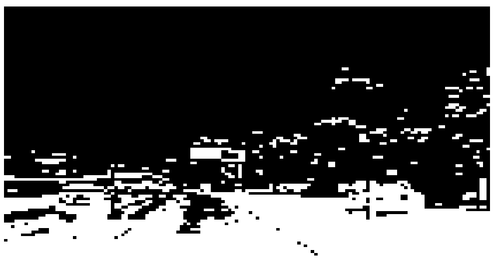
Eroded image:



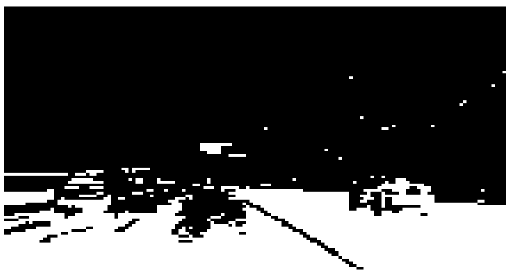
2.

Original image:

Dilated image:



Eroded image:



3.

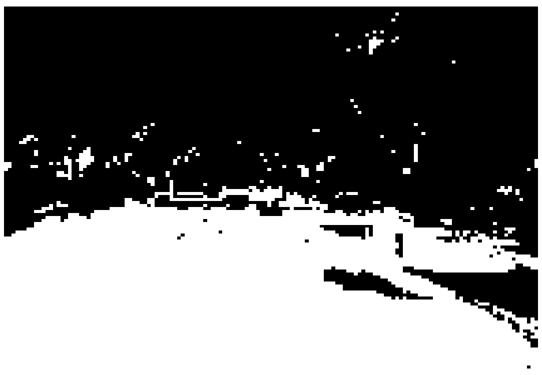
Original image:

Dilated image:

Eroded image:

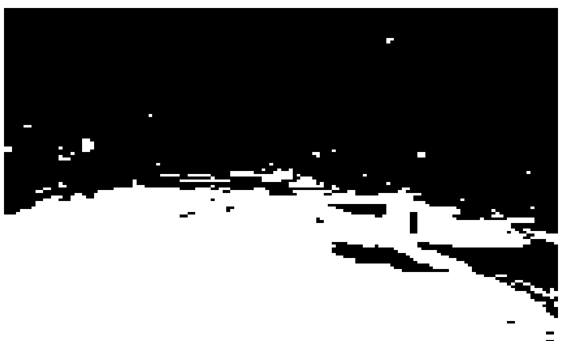
4.

Original image:



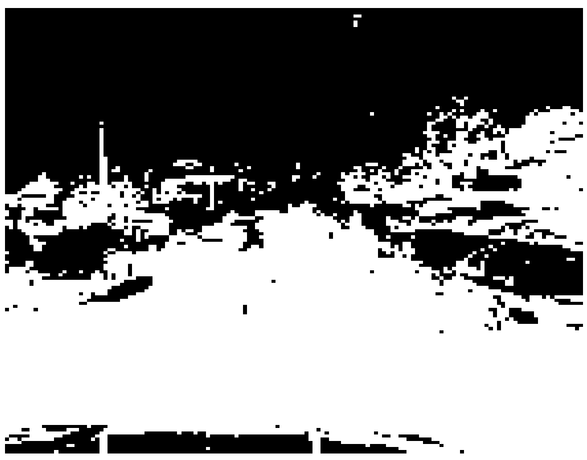
Dilated image:

Eroded image:

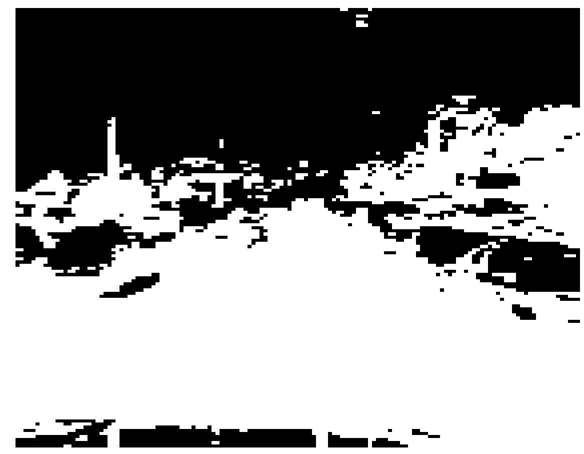


5.

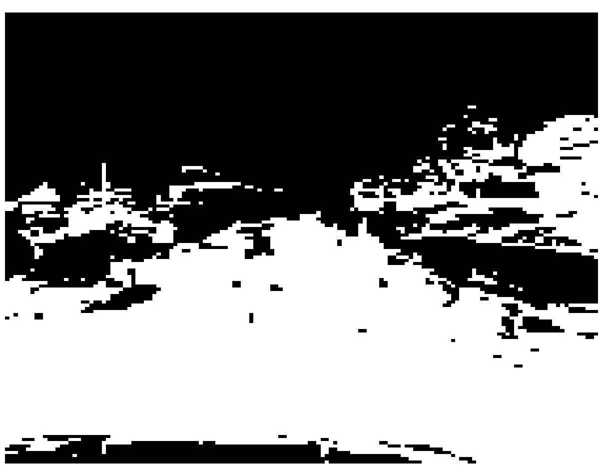
Original image:



Dilated image:

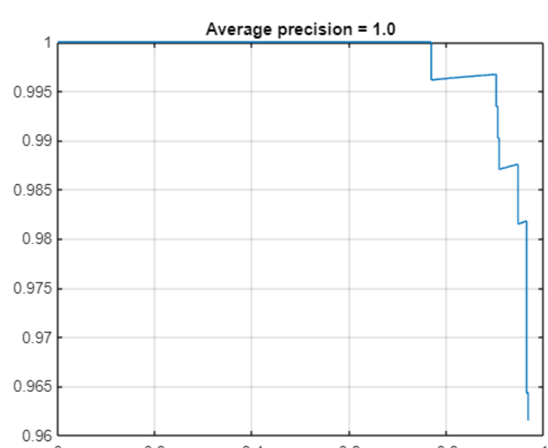


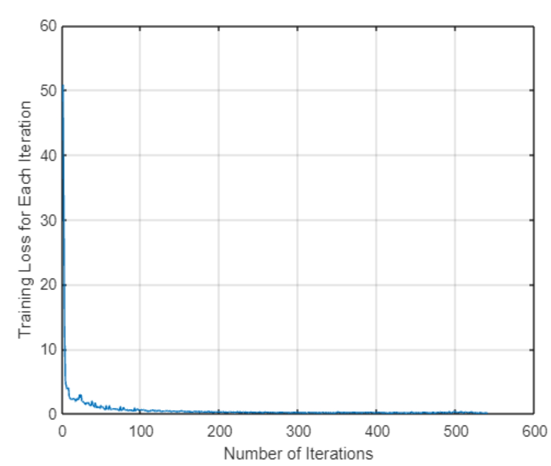
Eroded image:



Training the images:

Graph results for object detection:





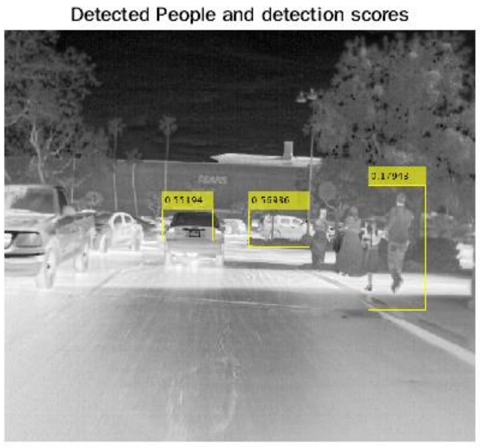
1.Original image:

2.

Original image:

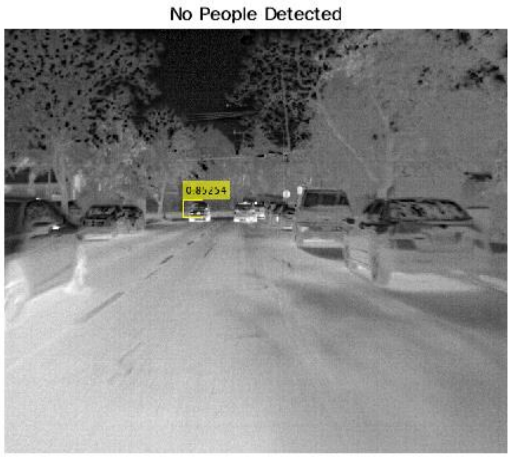
3.

Original image:



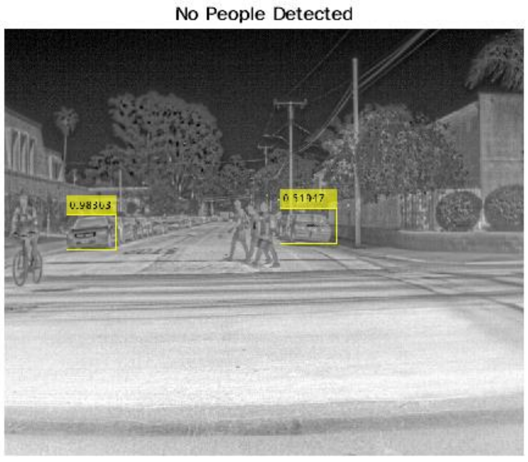
4.

Original image:



5.

Original image:



Experimental Results Analysis:

The performance of the proposed system is evaluated for various types of images in different environment from our dataset. Every image is processed using different image processing techniques like image enhancement using histogram equalization, restoration using IFFT, image segmentation using grey-level thresholding and morphological processing by dilation and erosion. After processing the dataset image, we imported pre-existing image sets for training.

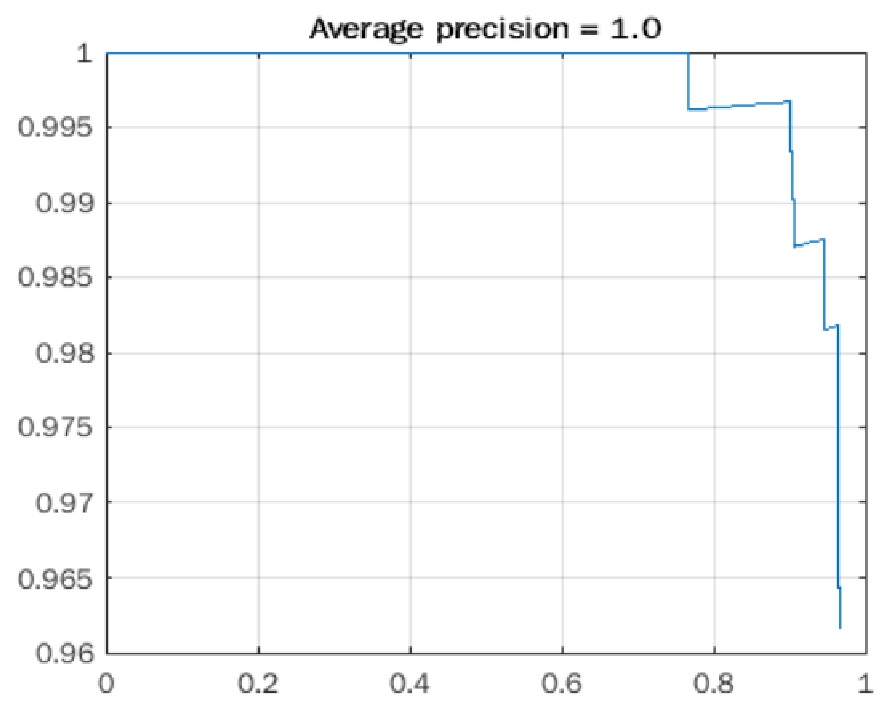
For training our model we use YOLOv2 which is a single-stage real-time object detection model with Darknet-19 as a backbone, batch normalizer, using anchor boxes to predict the bounding boxes. This transfer learning method allowed us to build models in accordance with similar and a larger dataset (vehicleTrainingData.mat). The vehicle training data is loaded into the workspace and the training samples are stores in a data directory. We then randomly shuffle data for training. We use preinitialized YOLO v2 object detection network (yolov2VehicleDetector.mat). The layer inspected has about 25x1 layer arrays containing layers for the input image, convolution, batch normalization, max pooling, ReLU, YOLO v2 transform layer, 4 anchor output.

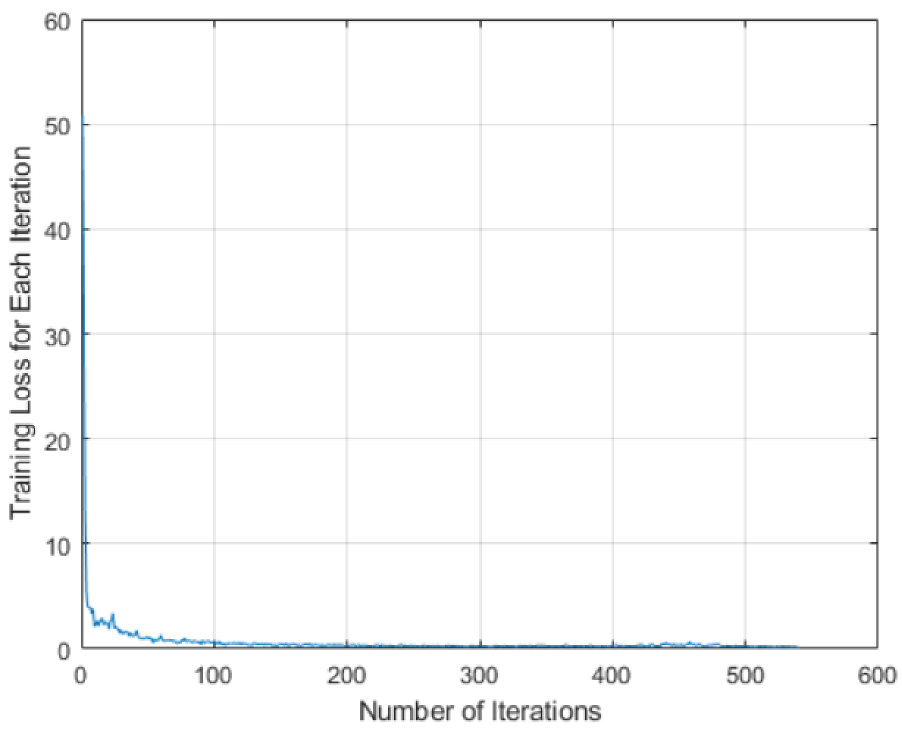
```
25x1 Layer array with layers:

 1   'input'               Image Input               128x128x3 images
 2   'conv_1'              Convolution               16 3x3 convolutions with stride [1  1] and padding [1  1  1  1]
 3   'BN1'                 Batch Normalization       Batch normalization
 4   'relu_1'              ReLU                      ReLU
 5   'maxpool1'            Max Pooling               2x2 max pooling with stride [2  2] and padding [0  0  0  0]
 6   'conv_2'              Convolution               32 3x3 convolutions with stride [1  1] and padding [1  1  1  1]
 7   'BN2'                 Batch Normalization       Batch normalization
 8   'relu_2'              ReLU                      ReLU
 9   'maxpool2'            Max Pooling               2x2 max pooling with stride [2  2] and padding [0  0  0  0]
10   'conv_3'              Convolution               64 3x3 convolutions with stride [1  1] and padding [1  1  1  1]
11   'BN3'                 Batch Normalization       Batch normalization
12   'relu_3'              ReLU                      ReLU
13   'maxpool3'            Max Pooling               2x2 max pooling with stride [2  2] and padding [0  0  0  0]
14   'conv_4'              Convolution               128 3x3 convolutions with stride [1  1] and padding [1  1  1  1]
15   'BN4'                 Batch Normalization       Batch normalization
16   'relu_4'              ReLU                      ReLU
17   'yolov2Conv1'         Convolution               128 3x3 convolutions with stride [1  1] and padding 'same'
18   'yolov2Batch1'        Batch Normalization       Batch normalization
19   'yolov2Relu1'         ReLU                      ReLU
20   'yolov2Conv2'         Convolution               128 3x3 convolutions with stride [1  1] and padding 'same'
21   'yolov2Batch2'        Batch Normalization       Batch normalization
22   'yolov2Relu2'         ReLU                      ReLU
23   'yolov2ClassConv'     Convolution               24 1x1 convolutions with stride [1  1] and padding [0  0  0  0]
24   'yolov2Transform'     YOLO v2 Transform Layer.  YOLO v2 Transform Layer with 4 anchors.
25   'yolov2OutputLayer'   YOLO v2 Output            YOLO v2 Output with 4 anchors.
```

The network training is configured using the training options. To train the YOLO v2 network, we use single CPU with different object classes using the command - `[detector,info] = trainYOLOv2ObjectDetector(ds,lgraph,options);`

```
Training on single CPU.
|========================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Mini-batch  |  Base Learning  |
|         |             |   (hh:mm:ss)   |     RMSE     |     Loss     |      Rate       |
|========================================================================================|
|       1 |           1 |       00:00:01 |         7.13 |         50.8 |          0.0010 |
|       2 |          30 |       00:00:14 |         1.35 |          1.8 |          0.0010 |
|       4 |          60 |       00:00:27 |         1.13 |          1.3 |          0.0010 |
|       5 |          90 |       00:00:39 |         0.64 |          0.4 |          0.0010 |
|       7 |         120 |       00:00:51 |         0.65 |          0.4 |          0.0010 |
|       9 |         150 |       00:01:04 |         0.72 |          0.5 |          0.0010 |
|      10 |         180 |       00:01:16 |         0.52 |          0.3 |          0.0010 |
|      12 |         210 |       00:01:28 |         0.45 |          0.2 |          0.0010 |
|      14 |         240 |       00:01:41 |         0.61 |          0.4 |          0.0010 |
|      15 |         270 |       00:01:52 |         0.43 |          0.2 |          0.0010 |
|      17 |         300 |       00:02:05 |         0.42 |          0.2 |          0.0010 |
|      19 |         330 |       00:02:17 |         0.52 |          0.3 |          0.0010 |
|      20 |         360 |       00:02:29 |         0.43 |          0.2 |          0.0010 |
|      22 |         390 |       00:02:42 |         0.43 |          0.2 |          0.0010 |
|      24 |         420 |       00:02:54 |         0.59 |          0.4 |          0.0010 |
|      25 |         450 |       00:03:06 |         0.61 |          0.4 |          0.0010 |
|      27 |         480 |       00:03:18 |         0.65 |          0.4 |          0.0010 |
|      29 |         510 |       00:03:31 |         0.48 |          0.2 |          0.0010 |
|      30 |         540 |       00:03:42 |         0.34 |          0.1 |          0.0010 |
|========================================================================================|
Detector training complete.
*************************************************************************
```

The RMSE is used to estimate the positional accuracy. We can verify the training accuracy of the detector by inspecting the training loss for each iteration and the graph is obtained.





Images are classified using faster RCNN network to detect cars in an image and annotate with detection scores. The detector is uses modified version of MobileNet-v2 network architecture. We use functions from the deep learning toolbox for the process.

To detect people in the image, we use the object peopleDetector that uses Histogram of Oriented Gradient feature and Support Vector Machine (SVM) classifier.

We load the image and store the locations of the bounding boxes and their detection scores.

Dataset	Scores
Image 1	0.53936,0.1169,0.51619
Image 2	0.99877,0.92321
Image 3	0.55194,0.58336,0.17913
Image 4	0.85254
Image 5	0.98303,0.51947

Dataset:

Our Dataset contains over 14,000 thermal images, both synced annotated thermal imagery and non-annotated RGB imagery for reference. The camera centrelines approximately 2 inches apart and collimated to minimize parallax.

https://www.flir.com/oem/adas/adas-dataset-form/

Conclusion:

In order to detect objects and human beings using thermal image processing we must follow the given steps-

- For image enhancement, we will be using Histogram equalization adjusts the contrast of an image by spreading out most frequent pixel intensity values or stretching the intensity range of the image.
- For image segmentation we use grey level thresholding This divides all the pixels of the input image into 2 groups one is pixels having intensity value lower than threshold and then pixels having intensity value greater than threshold. Deep learning methods and Fourier transform helps in extracting the important features of the image.
- Convolutional neural networks help in detecting the objects with high accuracy and precision.
  Using thermal imaging to detect objects is widely becoming useful to help the visually impaired. While the methods are highly accurate and specific, there is still undergoing development to achieve 100% accurate results.
- For training the dataset we use YOLO (you only look once) V2 Network algorithm. It uses a single stage object detection model and is more accurate as compared to YOLO v1 Network. We use a high resolution classifier (CNN) and the use of anchor boxes to predict the bounding boxes and classify the features for recognition.

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