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https://www.jisem-journal.com/ **Research Article**

A Comparison of the VGG19, InceptionV3, NASNetMobile, and ResNet50 Architectures for Object Classification in Thermal Images

Haider Ali Muften[1], Ali Retha Hasoon Khayeat[2]
[1],[2] College of Computer Science and Information Technology
haider.ali@s.uokerbala.edu.iq
ali.r@uokerbala.edu.iq

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ABSTRACT

Identifying objects within thermal images is of paramount importance across diverse applications, employing sophisticated machine learning algorithms for precise object localization. Thermal imaging cameras excel at capturing the infrared radiation emitted by objects, enabling visibility through obstacles such as smoke, fog, and darkness. Navigating through thermal images to discern objects mirrors the challenges encountered in traditional visual image analysis.

This paper focuses on the development of a convolutional neural network model designed specifically to address multiple classification challenges using contrast-enhanced thermal images processed with CLAHE (Contrast Limited Adaptive Histogram Equalization). The precision, F1-score, and recall of popular architectures, namely VGG19, ResNet50, InceptionV3, and NASNetMobile, are rigorously evaluated on a curated selection of contrast-enhanced CLAHE images. The findings reveal varying levels of accuracy across these models, with VGG19 achieving a notable 97%, InceptionV3 and NASNetMobile at 95%, and ResNet50 registering an accuracy of 94%. This research present significant insights into the utilization of transfer learning methodologies for the classification of thermal imagery.

Keywords: VGG19, ResNet50, InceptionV3, NASNetMobile, thermal images, object classification.

1. Introduction

Thermal cameras have been increasingly used in surveillance systems in recent years [1]. Thermal imaging is a useful supplement to optical imaging since it can find things in low light and at night [2]. In contrast to thermal imaging, which is produced when the thermal camera focuses infrared radiation on a particular region, visible imaging is produced by the reflection of light from the object. Color maps of photos are used to construct thermal images of that particular location, and the strength of different colors varies from thermal camera to thermal camera [3]. Because of its many uses and recent technology advancements, object detection has been receiving more and more attention in recent years [4].

In recent years, there has been a significant increase in the utilization of infrared cameras in surveillance systems [1]. Thermal imaging is a valuable complement to visual imaging because of its capacity to detect objects in low-light and nocturnal circumstances [2]. There are fundamental differences in the manner in which visible imaging and thermal imaging capture and represent images. Imaging by visible light relies on the fact that objects reflect light which is perceived by the human eye by a device known as a camera. On the other hand, thermal imaging detects infrared radiation as emitted by objects at the temperature level. Thermal camera will capture infrared rays (heat rays) and focus those rays on a certain area, and thermal images which represent the distribution of temperature across an object or scene are generated. The thermal images are given as color maps in which each color represents a range of temperatures. [3]. Thermal imaging, which identifies objects in low light and darkness by detecting infrared radiation and generating temperature-related images, is a valuable complement to optical imaging. Targets are identified using extraction to isolate certain sections [1].

The process of identifying items within an image is accomplished through a technique known as object detection [4]. The importance of object detection and classification in surveillance and pedestrian detection has increased significantly. Traditional detection techniques often use visible range cameras for accurate object analysis and identification. Visible cameras capture sharp silhouettes and significant picture contrast, enabling effective object recognition in applications like surveillance and pedestrian detection [5]. Thermal imaging is a valuable complement to optical imaging, detecting objects in low-light and dark conditions by sensing infrared radiation and generating temperature-related images. Targets are identified by isolating specific areas through extraction [1]. Identifying objects is the process of scanning and searching for an item within a video or image in computer vision [6]. Object detection consists of two main parts: classification and object localization. Classification assigns a class to detected objects, while localization defines their position and size. To achieve generalization, a large amount of training data is required. Object detection systems create models based on diverse training data for accurate detection across different scenarios [7]. The choice of an object detection approach is contingent upon the specific problem that needs to be addressed. Different There are trade-offs with detectors in terms of detection findings' amount of detail, accuracy, and speed. Selecting the most suitable approach involves considering these trade-offs based on the requirements and constraints of the particular application or scenario [8].

2. Related work

A study comparing visible-spectrum and thermal images using a faster R-CNN found that visible spectrum images were as accurate during the day as thermal camera images. Thermal images were more accurate at night, with an accuracy of 75.9% for thermal photos of a four-wheeler compared to 24.3% for visible spectrum photographs. Thermal photos also showed better accuracy in scenarios like 2-wheeler, traffic-light, and person, with 58.5%, 61.7%, and 77.1% respectively. The study suggests that considering various times, seasons, and weather conditions can improve the system's usefulness [6].

The study compared two models, SSDMobileNetV1 and SSDMobileNetV2, for object detection and classification in thermal camera pictures. Both models performed well in identifying objects from cars, bicycles, and people. Model 2 outperformed Model 1 in most assessment parameters, with 83% and 99% accuracy levels for automobiles and 98% and 99% for people, respectively. Model 2 had a detection rate of 59%, while Model 1 had 0% and 76% accuracy rates for bicycles. Both models accurately recognized small and medium-sized items, with Model 2 often having the best success rates [1].

The Mask-RCNN architecture utilizes the Resnet-101 framework for object localization. The KAIST multispectral dataset is employed for training and evaluation purposes. [9].

The Haar-Cascade classifier approach was used to detect human presence in thermal pictures, revealing that higher camera-object distance decreases detection recall and precision. Multiple human objects can be detected, but false positives occur when other objects with similar properties, such as painted walls or infrared shadows, are detected. The accuracy and recall of human object recognition decrease with increasing camera distance and posture angle, with the worst performance occurring at a 90° pose angle. Individuals in front of, adjacent to, or overlapped with each other have 100% detection performance. However, additional objects with similar traits can be recognized as human. Infrared shadow objects reflected by painted walls or glass mirrors can also be used to identify human identity [10].

A novel method utilizing the Shape Context Descriptor (SCD) and the Adaboost cascade classifier framework is presented for pedestrian recognition in thermal images. The approach surpasses conventional rectangular features in most phases, with a detection rate over 70% with a false positive rate of approximately 20 (5%). The suggested detector exhibits a 30% detection rate, around 40 false positives, and a 10% false positive rate at an 80% detection threshold. It employs a rectangular feature-based detector with a 45% detection rate, integrating SC and boosting for resilient human information representation in thermal pictures.[11].

Rodin, C.D., et al [12], The GMM is employed to distinguish foreground objects from the background, and a CNN is trained to evaluate photos of boats. The k-fold method utilizing five folds achieves an average accuracy of 92.5%. Convolutional Neural Networks (CNN) were utilized to assess photographs of boats from diverse datasets, attaining a certainty of 100% about their presence.

3. Methods and materials

Following the completion of the studies, we went on to excite the participants in this field with precise and topical research, all within the framework of identifying the suitable model for classifying living things. In order to comprehend our work, we will build four classification systems VGG19, ResNet50, NASNetMobile, and InceptionV3—using a collection of contrast-enhanced thermal pictures employing CLAHE technology. To create the optimal model, data augmentation was applied to the improved image collection. In order to complete this job, we decided to break it down into main phases. Each of these processes will be thoroughly detailed in the article that follows.

3.1 Dataset

In the context of the machine learning process, collecting the data is one of the crucial steps when it comes to models with deep learning, given that they are designed to work with a large amount of data that needs low feature extraction. In order to use this, we had used a dataset from Kaggle ('https://www.kaggle.com/datasets/albertofv/flir-thermal-images-dataset-reduced ').There are thermal images from FLIR cameras in various formats provided in the dataset. They consist of raw images that are directly captured by the sensor and enhanced images which are processed using the particular FLIR algorithms. The roved images offer direct thermal data and they are enhanced as best as possible to offer clear visibility, better contrast, and so on, all this requires them to be applied in different applications. Since image formats are diverse, it can be examined and trained model with both unprocessed and preprocessed data, so the model can adapt to different levels of image quality. However, this dataset is very useful for object detection, classification as well as anomaly detection in thermal imaging.

After cropping the images, we only obtained 2956. In fact, they consist of four classes: person, car, nothing, and mixed (person and car), with a file containing 739 for each type. However, our research seeks to identify a model that provides satisfactory results for the classification of thermal images enhanced with CLAHE.

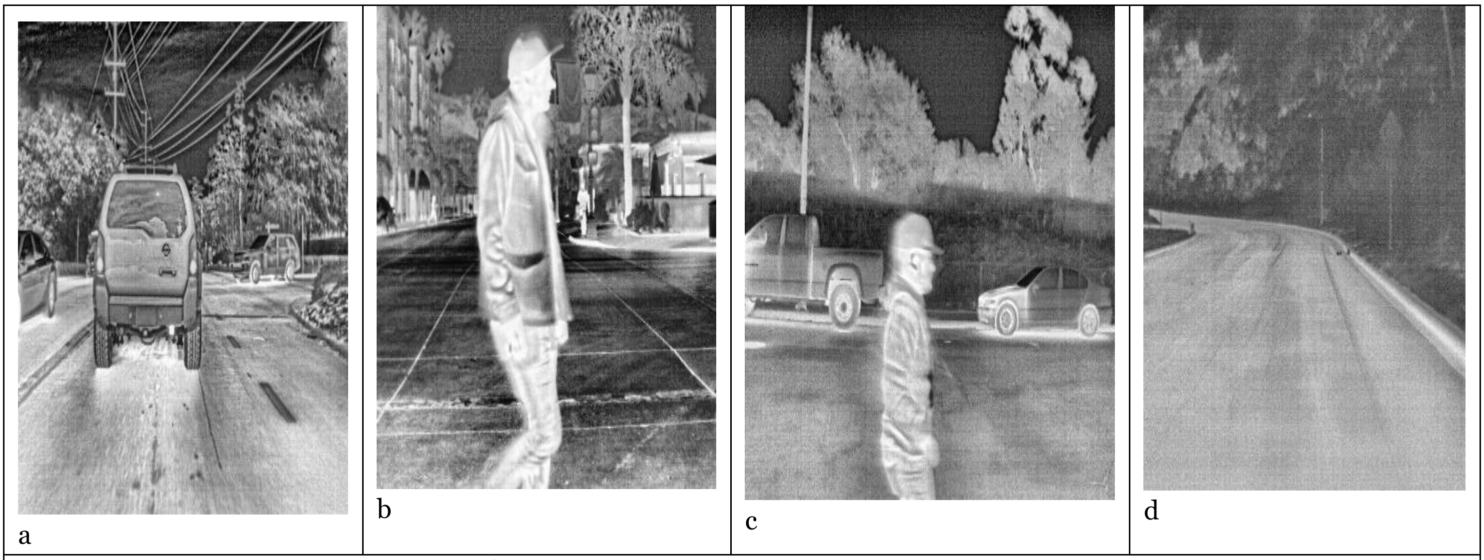


Figure 1: Example of images, (a) car (b) person,(c) mixed(person and car),(d) None

3.2 Image preprocessing

For deep learning applications, data preprocessing is essential, especially to obtain precise and accurate results. In the case of thermal images, which are often of poor quality and unusable due to various problems including fog, dust storms, etc. For all intents and purposes, we chose two techniques for preprocessing the image set: one focused on improving image quality so that classifiers could accurately classify presented cases, and the other on generating many images through data augmentation [13].

3.2.1 Data augmentation

Data augmentation is one of the most popular methods for producing a large number of images. the issue of insufficient data, particularly when gathering is difficult. This study includes numerous attributions that provide extra photographs; the additional criteria are included in the following table. [14].

Method	Setting
Rotation range	20
Width shift range	0.2
Height shift range	0.2
Shear range	0.2
Zoom range	0.2
Horizontal flip	True
Fill mode	'nearest'

Table 1: The classic data augmentation method's parameter settings.

3.2.2 Contrast Limited Adaptive Histogram Equalization (CLAHE)

A technique for equalizing each segment of a histogram involves splitting the image into small regions known as blocks, which are typically 8x8 in size. This strategy is commonly used to improve the contrast quality of photographs, particularly those with low contrast. Furthermore, it is used to reduce the problem of noise amplification caused by the use of HE techniques. The clipping limit (CL) and block size (BS) of the CLAHE method are two critical parameters that influence the quality of the enhanced image. Because the input image had a low intensity to begin with, the image brightness increased as CL increased. As the level of confidence increases, the histogram grows flatter. Clipping limitations increase the dynamic range and visual contrast.

[15].

a b

Figure 2: Example of images, (a) Before using CLAHE (b) After using CLAHE

4. EXEREMENTAL

3.3 Classification

Transfer learning (TL) employing convolutional neural networks can enhance performance on a novel task by utilizing knowledge from prior assignments. It has significantly improved thermal image analysis by mitigating data sparsity and optimizing time and hardware use.[16].

3.3.1 ResNet50

One residual network is called ResNet50. consisting of 26 million parameters and fifty layers. Microsoft debuted a model of a deep convolution neural network called Indeed in 2015 [17]. We learn residuals in the residual network, which is the removal of acquired characteristics from the input layers, as opposed to learning features. ResNet establishes a deep network by directly connecting the nth layer's input to the (n+x)th layer, enabling the stacking of further layers. In our experiment, we employed a pre-trained ResNet50 model and improved it. The ResNet50 architecture is shown in Figure 3.

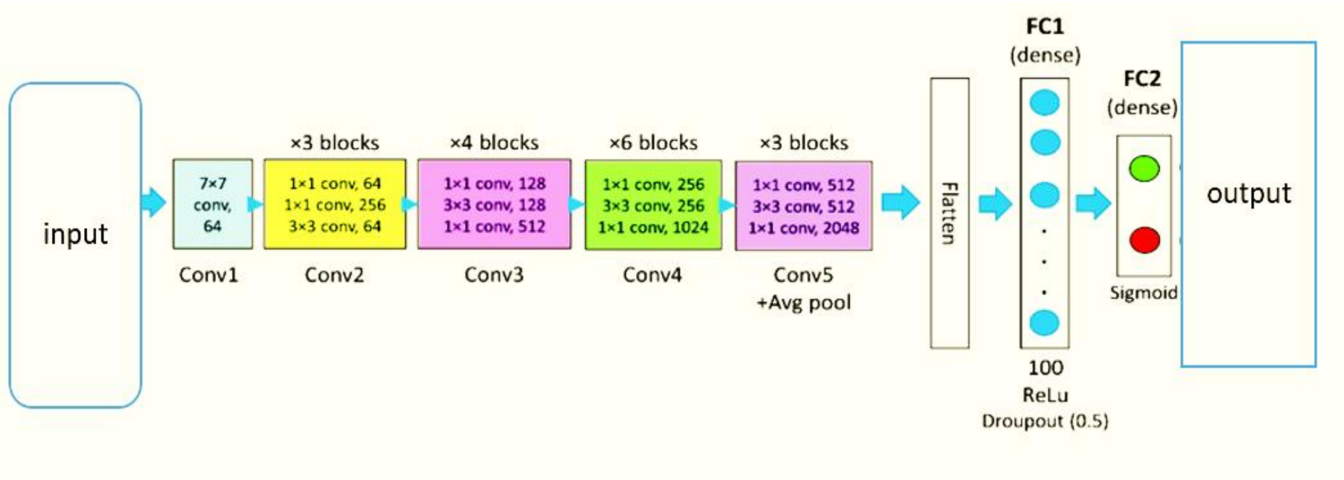


Figure 3: ResNet-50 model architecture.

3.3.2 VGG19

Nineteen is the VGG19 model weighted layers (refer to Figure 4) that are composed of three fully interconnected layers (fc) and 16 convolutions. A three-channel image serves

as the model's input with dimensions of 224 × 224 that has had its average RGB value removed. The layers of convolution use a 3 × 3 slot size, with a stride and padding of 1 pixel each. Five max-pooling layers with a 2x2 core size and a 2-pixel stride make up the array [18].

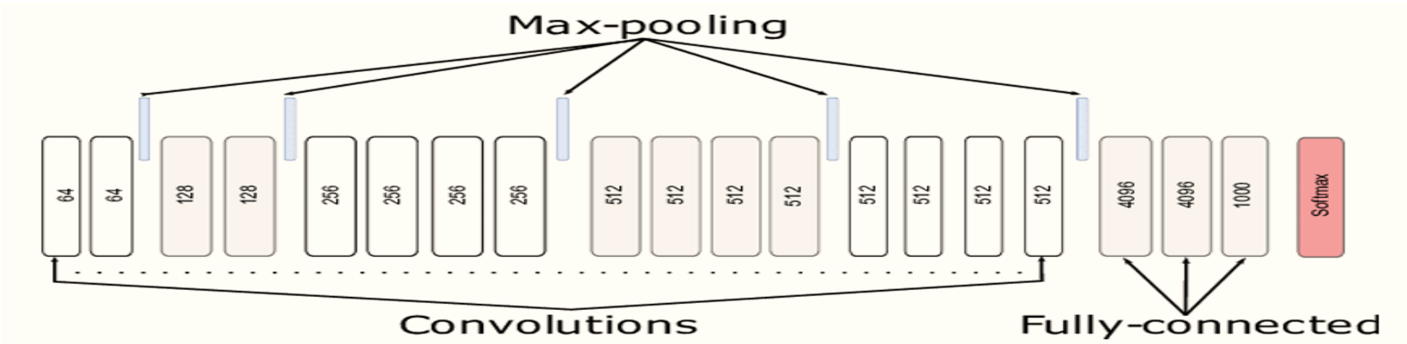


Figure 4: VGG19 model architecture

3.3.3 NASNet-Mobile

NASNet-Mobile is a CNN trained on over a million images from the ImageNet database, capable of classifying photographs into categories of 1000 objects. For a variety of photos, it has acquired extensive feature

representations, making it suitable for medical imagery. NASNet-Mobile was trained using

TensorFlow, allowing for the restoration of features and retaining some layers for the task. The features learned are general and can be used for other image classification tasks. To resize the input data, the network is pre-processed to 224-by-224, reusing initial and middle layers and retaining task-specific layers from the custom model.

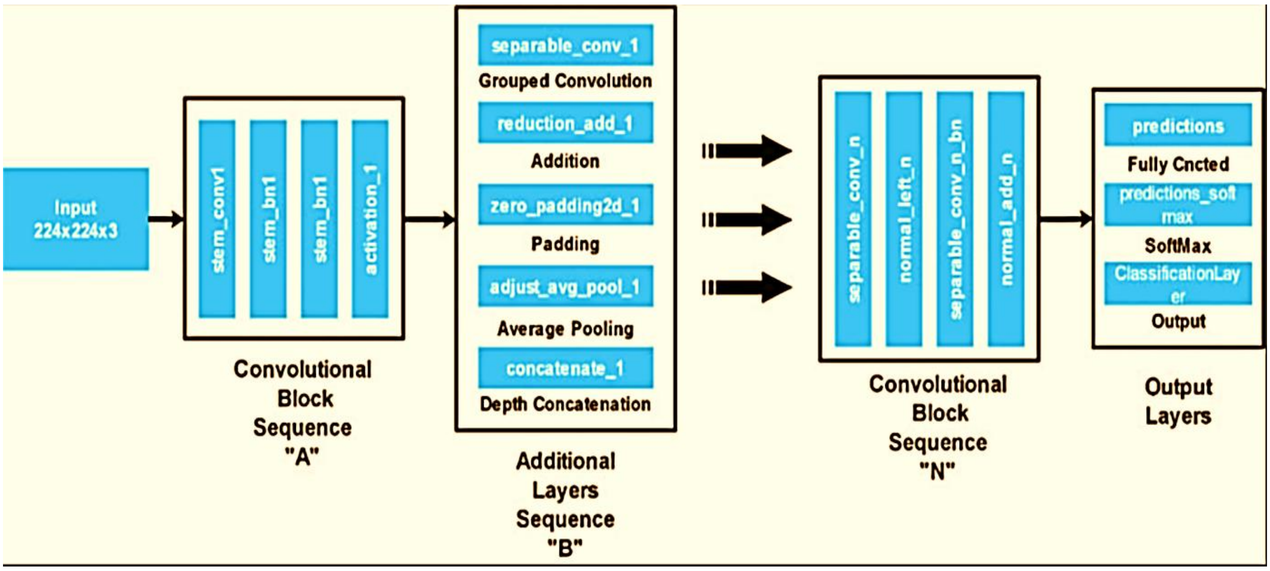


Figure 5: NASNet-Mobile model architecture

3.3.4 Inception-v3

As a deep neuronal structure the Inception v3 network model has to be practiced on a machine with little configuration out of space for days, that is why we cannot practice it. There are courses to Tensorflow that allow us to retrain the last Layer of Inception from new categories with transfer learning. So with transfer learning, we retrain the last layer of the model of Inception-v3 but keep parameters of all the other layers. The number of categories in the dataset equals the number of output nodes in the final layer. For instance, in the Inception-v3 where the ImageNet dataset consists of 1000 classes, the last layer of the original Inception-v3 contains 1000 output nodes.

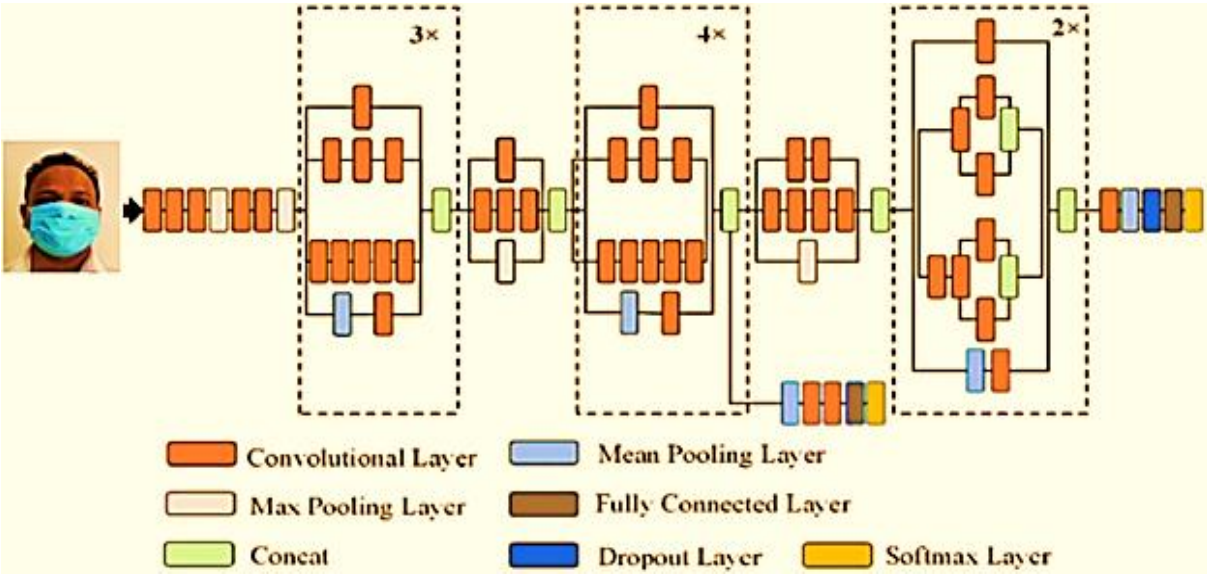


Figure 6: Inception-v3 model architecture

3.4 Hyper Parameter

Its to determine the parameter values to enter in order to create the classification job since the numbers entered would frequently affect the outcome. The values presented in the following table represent the optimal results. We conducted numerous trials with carefully selected parameters, adjusting the numbers in each iteration, until we achieved the best overall performance. [19]

Table 2: Hyperparameters that we added to our classification models					
Data	Batch size	Nb of Epochs	Type of optimizer	Early stopping	Type of metrics
Train : 70% Val : 10% Test : 20%	Train : 24 Val : 24 Test : 24	100	SGD (0.001)	10	accuracy

5. Performances Metrics

In this paper we use confusion matrix Specifically, the parameters include: True Positive (TP), which indicates correctly labeled thermal imaging data; False Negative (FN), representing misclassified normal image data; False Positive (FP), showing incorrectly classified thermal image data; and True Negative (TN), which indicates correctly classified normal image data.

5.1 Accuracy, Precision, Sensitivity (Recall), F1 Score

$$\text{acuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

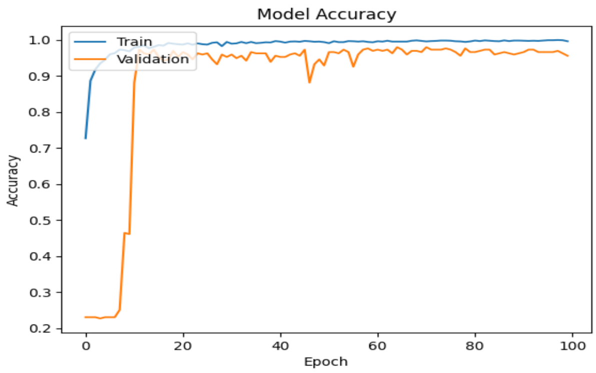
$$\text{F1 Score} = \frac{2.\ TP}{2.\ TP+FP+FN} \quad (4)$$

6. Results

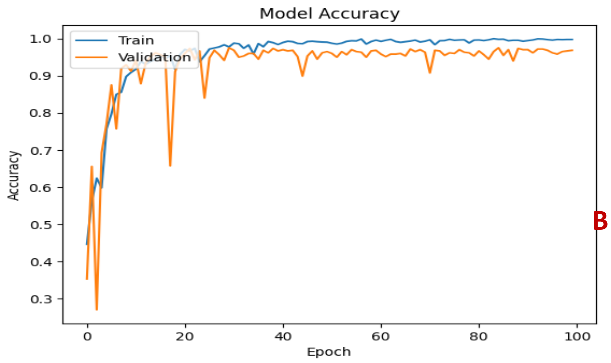
Table 3 shows the accuracy, F1-Score, precision and recall based on the thermal image dataset. Figure 7,8 and 9 show the evolution of accuracy and loss evaluation and Confusion matrices based on the thermal image dataset.

Table 3: View model accuracy results

Type model	Accuracy	F1-Score	Precision	Recall
VGG19	0.97	0.97	0.97	0.96
InceptionV3	0.95	0.95	0.96	0.95
NASNetMobile	0.95	0.95	0.95	0.95
ResNet50	0.94	0.94	0.95	0.94



A



B

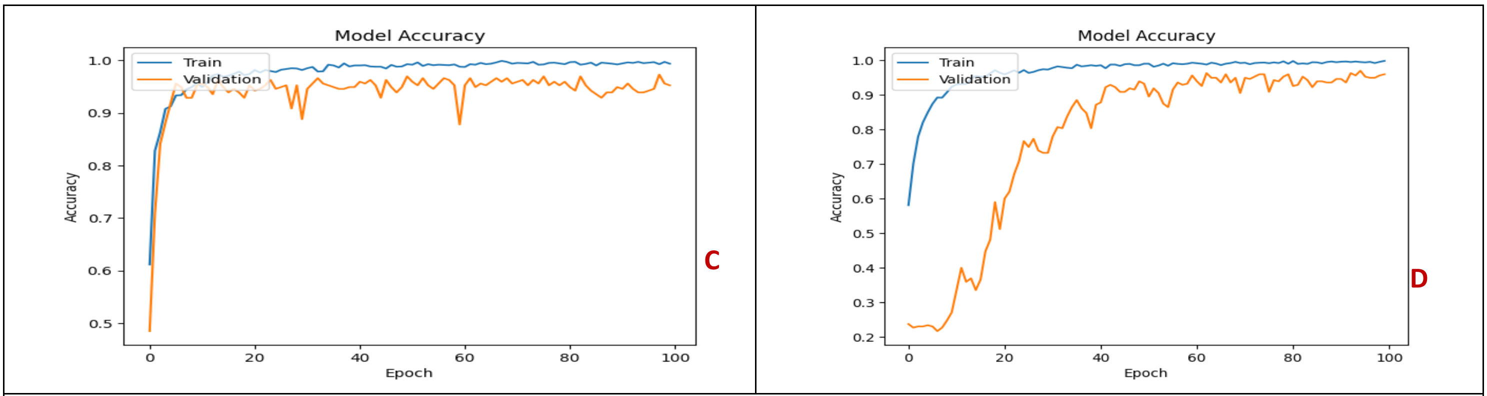


Figure 7: Accuracy evolution of the models (a: Resnet50, b: VGG19, c: InceptionV3, d: NASNetMobile)

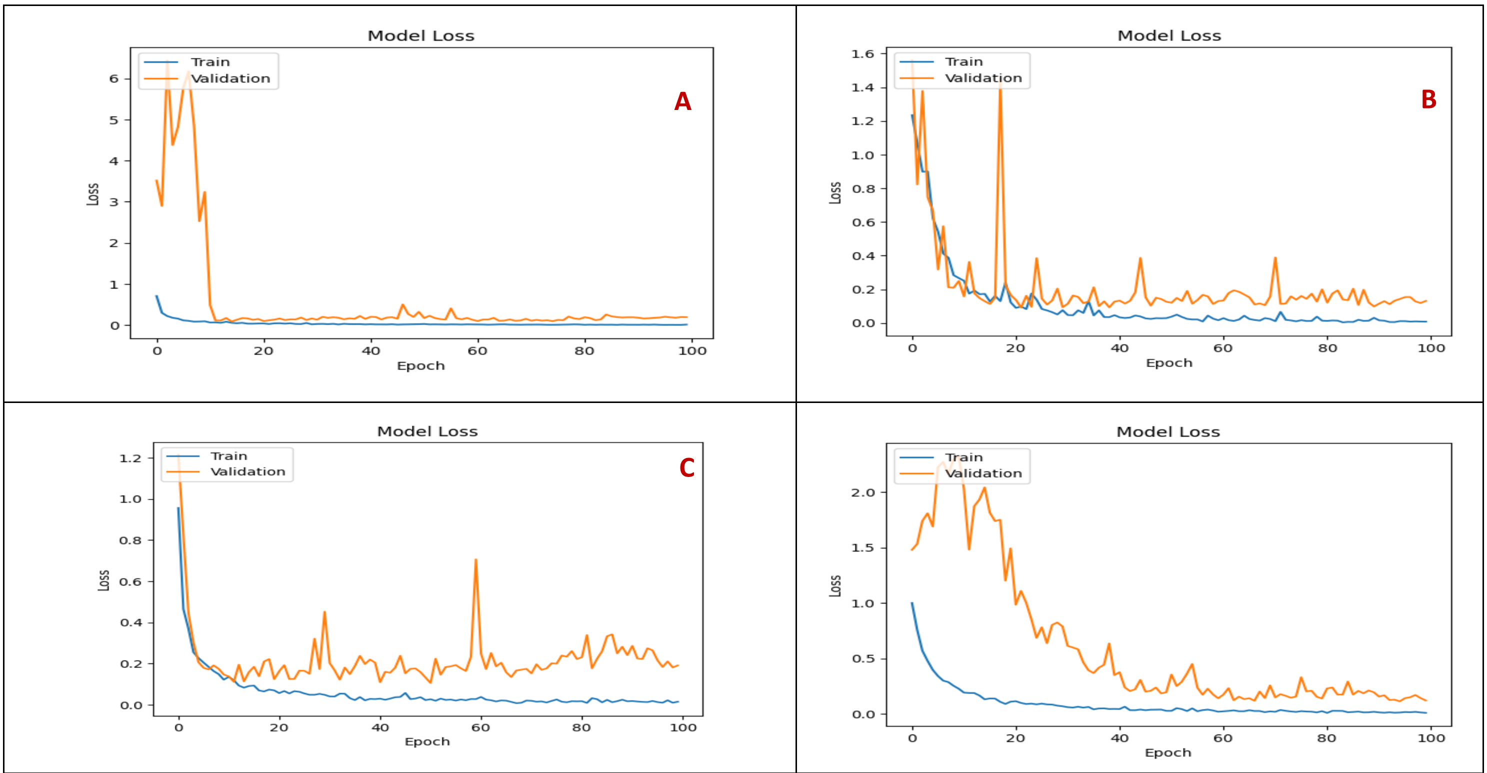
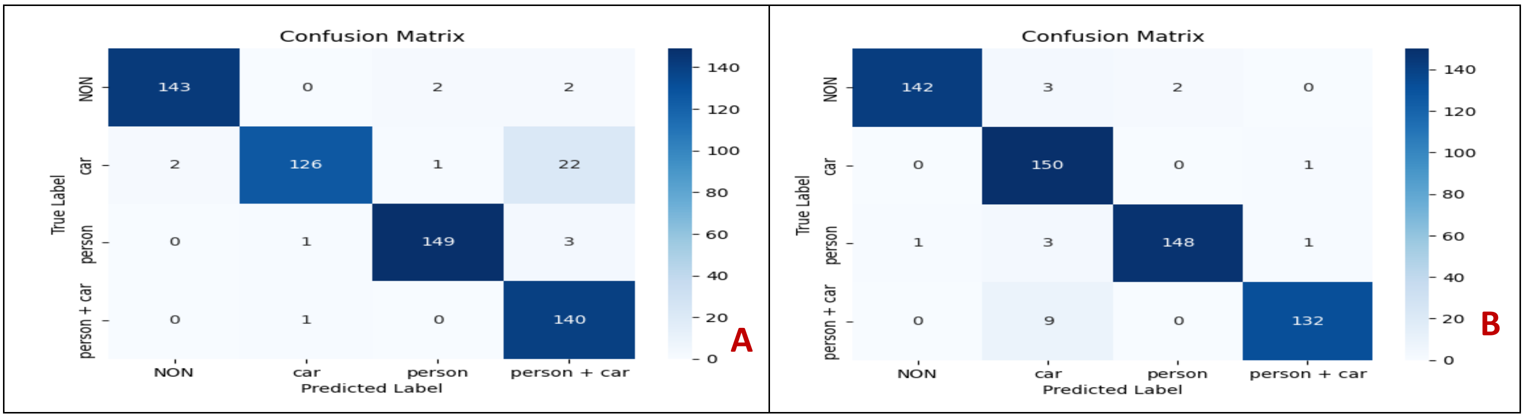


Figure 8: Loss evolution of the models (a: Resnet50, b: VGG19, c: InceptionV3, d: NASNetMobile)



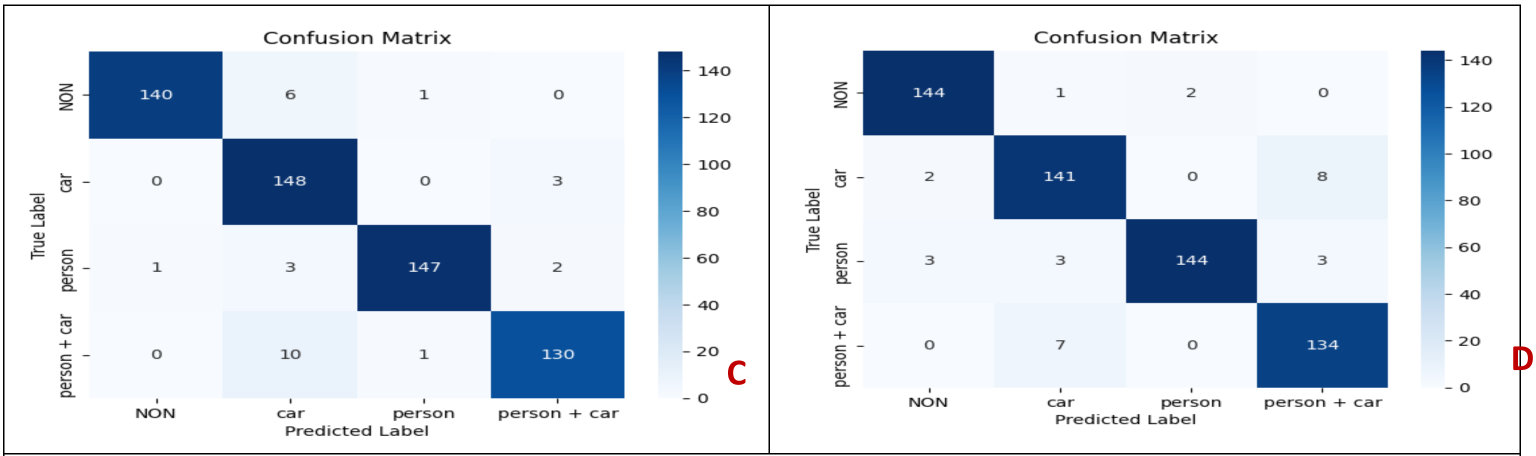


Figure 9: Confusion matrices of the models (a: Resnet50, b: VGG19, c: InceptionV3, d: NASNetMobile)

7. Conclusion and future work

Based on the data, it is evident that this investigation met our objectives and led to very pertinent findings. When it comes to improved picture contrast scenarios, the VGG-19 design performs the InceptionV3, NASNetMobile, and Resnet50 architectures in terms of efficiency for the thermal image classification job. The findings of using CLHAE technology showed that the CLAHE approach is a highly useful method for increasing the thermal image's contrast without sacrificing any of its information.

In future work, we will use more accurate for the segmentation and classification algorithms such as yolov8.

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