Infrared Imaging for Human Thermography and Breast Tumor Classification using Thermal Images

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***Abstract*— Human thermography is considered to be an integral medical diagnostic tool for detecting heat patterns and measuring quantitative temperature data of the human body. It can be used in conjunction with other medical diagnostic procedures for getting comprehensive medication results. In the proposed study we have highlighted the significance of Infrared Thermography (IRT) and the role of machine learning in thermal medical image analysis for human health monitoring and various disease diagnosis in preliminary stages. The first part of the proposed study provides comprehensive information about the application of IRT in the diagnosis of various diseases such as skin and breast cancer detection in preliminary stages, dry eye syndromes, and ocular issues, liver disease, diabetes diagnosis and last but not least the novel COVID-19 virus. Whereas in the second phase we have proposed an autonomous breast tumor classification system using thermal breast images by employing state of the art Convolution Neural Network (CNN). The system achieves the overall accuracy of 80% and recall rate of 83.33%.**

Keywords—Infrared Thermography, Deep Neural Networks, Thermal camera, Computer Aided Dignosis, Classification

I. Introduction

Thermal imaging is one of the most rapidly growing imaging techniques nowadays [1]. It can be described as a key method for measuring the spatial temperature of various materials, objects, and scenes. It plays a pivotal role in detecting abnormal temperature patterns of the human body. It works by absorbing IR radiations emitted from the human body and then generating heat energy indications with or without visible illumination conditions. The heat maps are generated in different color schemes such as iron, grayscale and rainbow thermals maps. These color maps are generally used to define different temperature ranges which eventually help us in identifying the health parameters of the human body. Fig. 1 shows the heat map in five different color maps of the thermal human face of the healthy subject. These images are acquired using an uncooled prototype thermal camera developed under the Heliaus EU project [29].

Thermography is the most common technique for acquiring valuable information using thermal cameras [2]. It collects information using an array of infrared sensors to read infrared energy emissions (surface temperature) to determine the operating conditions of different parts of the human body. It consists of two main components: Thermo and Graphy where Thermo refers to temperature patterns of the body and

Fig. 1. Visualization of different temperature color maps of a thermal facial image a) greyscale, b) glow, c) HSV, d) iron, e) rainbow.

Graphy refer to image acquisition techniques as shown in Fig. 2.

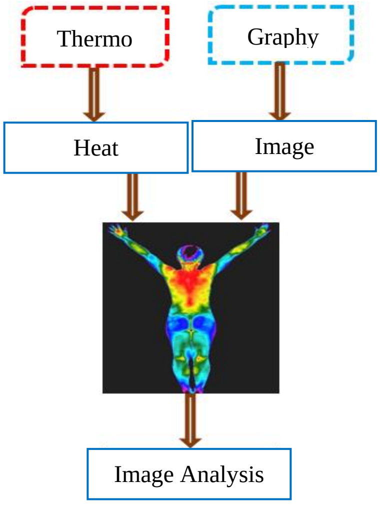

Fig. 2. Main components of human thermography.

Thermographic cameras usually detect radiation in the long-infrared range of the electromagnetic spectrum (roughly 9,000– 14,000 nm or 9–14 µm) and produce images using that radiation, which is generally referred to as thermograms. The amount of radiation emitted by an object increases with an increase in the temperature; therefore, thermography helps in analyzing the minute temperature variation patterns. In the overall classification, thermography can be divided into two main types which include active thermography and passive thermography. The passive thermography works by pointing the IR camera at the investigated body and checking whether the investigated body is at a lower or higher temperature than the background. Whereas, the active thermography approach is based on the excitation of the sample by applying external energy into it and subsequently measuring the thermal response from it. Therefore, active thermography is a fully dynamic process requiring different methods of image processing [3].

II. Background Research

The human body temperature is considered as a vital parameter that can be used for human health monitoring and various disease diagnosis. Measuring temperature with thermal camera systems comes with advantages such as non-contact and non-invasive diagnostic procedures. Moreover, thermography is a patient-friendly method and does not only provide conventional temperature measurement but also gives a comprehensive image of a patient's body temperature distribution which can be ultimately used to extract essential information regarding the overall body health [2]. Human clinical thermography depends on the exact examination of the skin surface temperature as an impression of the typical or anomalous physiology of the human [4]. There is a wide range of conventional medical imaging methods that give the field of internal imaging of the human body from outside inspection. For instance, we can remotely infuse and follow the radioactive isotopes to the body. The process of radiology works by utilizing the x-ray beam integrating with matter for plotting the internal structure of the body, yet these methods have weaknesses like low affectability and risk of harmful x-ray radiations, particularly when being emanated for a long time [5]. In comparison to this, infrared thermography is a patient-friendly technique, that provides a non-invasive detailed temperature distribution of human body. Thus it does not have destructive impacts of the harmful radiation which can be caused by conventional medical imaging procedures like x-ray, gamma rays, and Computed Tomography (CT) scans. In short, thermal imaging benefits us my analyzing abnormal temperature patterns of the human body that are the natural indication of any type of disease [6, 7]. However, the use of infrared thermal imaging in humans is dependent on different factors that need to be considered while acquiring such datasets. It includes environmental factors, individual factors dependent on human body intrinsic and extrinsic characteristics, and last but not least technical factors such as camera calibration, field of view (FoV) and subject distance from camera [20].

III. Human Thermography for Various disease Diagnosis

This section will mainly focus on various human disease detection using human thermography based health monitoring systems and diagnostic tools.

A. Infrared Thermography for Cancer Detection

Cancer or carcinoma tumors can be defined as one of the most fatal diseases in the human body. It is generally due to the abnormal growth of cells in any specific part of the body. It has the possibility of spreading to other parts of the body which can eventually lead to more serious medical conditions thus making it untreatable. Therefore, the detection of cancer in preliminary stages is a prime objective that allows doctors and specialists to perform specialized medical treatments to eventually cure the patients. Conventional medical procedures such as biopsy tests to check blood samples of infected areas of the body are often very painful for the patients. However, thermography can be efficiently used to detect different types of cancer in any part of the body. The process is painless as it provides non-contact and non-invasive diagnostic procedures. The process of thermography simply works by detecting the higher temperature in specific parts of the body thus the radiation compression also increases. It is due to more amount of heat generated from abnormal cancerous cells. Tumors can cause an increment in metabolism rate and blood flow which transports local stains with high temperatures in place that can be easily detected via the process of infrared thermography [2, 8]. IRT can be effectively used for different types of cancer detection in early stages which includes breast cancer detection [2], skin cancer detection [9], and brain tumor diagnosis [10].

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B. Infrared Thermography for Diabetes Diagnosis

Diabetes is the most rapidly growing disease in middle and low-income countries [27]. The more severe stages can cause paralysis and leg issues. The main reasons for these issues are low blood flow referred to as vascular disorder and the loss of feeling or weakness also knowns as neuropathy in medical terminology. During such type of disease patients normally undergoes abnormal skin temperature, thus making thermography an appropriate tool for diagnosis of vascular disorder or neuropathology. Such types of abnormal thermal patterns happen in the patient's leg and hands like temperature decrement in foot and toes. Generally, a diabetic patient suffers from higher temperature with average thermal readings of about 30.2 ± 1.3°C [15]. Therefore, infrared thermography plays a vital role in the initial diagnosis of diabetes in the human body which will eventually aid the doctors and specialists to provide appropriate treatment to their patients [11].

Vision Quest [12, 30] has developed a thermal optical imaging system capable of detecting early symptoms of diabetic peripheral neuropathy in the plantar foot, which accounts for about 25% of hospital stays among diabetes patients. The system works by recording the thermalized video of the patient's foot during recovery from cold provocation. The overall system comprises of high end and low noise infrared camera which is periodically calibrated to minimize thermal sensitivity to less than 0.50 °C. The system works by extracting the post images referred to as functional signals to detect dynamic changes in microvascular blood flow which are then analyzed. According to their initial research, the system can show visible statistical and significant differences between normal patients and subjects who have been diagnosed with peripheral neuropathy.

C. Thermography for Diagnosis of Liver Disease

Thermal Imaging especially near-infrared imaging is widely used for prodromal detection of chronic liver diseases. One such type of disease is liver fibrosis. It is a pathological process that can escalate to a more severe stage medically referred to as cirrhosis which eventually results in liver failure at its final stages. It is considered to be one of the major public health concerns that affect hundreds of millions of people in both developed and developing countries [13]. Therefore, early detection of liver fibrosis is of prime cause thus preventing them from the development of cirrhosis with chronic liver disease. Conventionally the level of fibrosis is examined by histological assessment using Mason's Trichrome stain performed by two different senior pathologists in a single-blind test and the severity of fibrosis is measured using Meavir Score shown in Table I.

TABLE I. Fibrosis Severity Scale

S:No	Level	Description
1.	F0	No fibrosis
2.	F1	Mild fibrosis
3.	F2	Moderate fibrosis
4.	F3-F4	Advanced fibrosis

But the process is time-consuming and requires years of experience for correct diagnosis. In fibrosis, De novo formation of such blood vessels can increase the surface temperature of the human liver however if the fibrosis advances to further stages i.e F3 cirrhosis, an excessive accumulation of connective tissue is observed in the liver and it results in the decrement of the surface temperature of the organ. These abnormal patterns of thermal temperature in lever can be easily detected by thermal imaging cameras which can be eventually used for the early diagnosis of liver fibrosis with high precision thus curing the patients from growing it into advanced stages [13].

D. Thermography for Eye Ocular Issues

Thermology is used in the field of human ophthalmology for the diagnosis of dry eye syndromes and ocular issues [14] by observing the eye physiology. The process of non-intrusive Infrared thermography (IRT) works by detecting the abnormal temperature behaviors of dry eye which is nearly about (32.38 ± 0.69°C). It is slightly higher as compared to the temperature of a healthy eye which is about (31.94 ± 0.54 °C) [15]. Generally, the horizontal temperature distribution in heathy eye organ is symmetrical and it is relatively low in the geometric center of the cornea as shown in Fig. 3 (image reproduced by the author's permission).

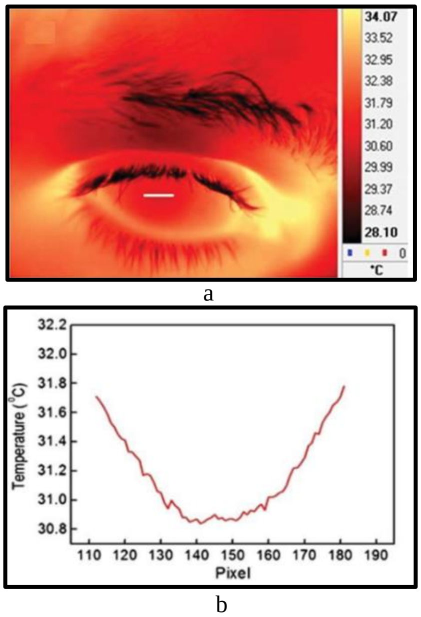

Fig. 3. Thermographic test image of a human eye, a) Horizontal temperature distribution of healthy cornea, b) Horizontal line in the graph indicates the thermal characteristics [15].

E. Infrared Imaging for Detecting Novel COVID-19 Virus

Currently, coronavirus has become one of the largest widespread disease throughout the world. According to the reported statistics and figures [16] around 194 countries [16] have been affected with more than 5.1 million cases all over the world and more than 330,000 [16] people died due to it. Medically it has been termed as COVID-19 and it has been declared as a pandemic from the World Health Organization (WHO) [28]. The symptoms of this disease appear in 2-14 days and the immune system of the affected person detects an infection that results in raise of core body temperature. Other symptoms of this virus include dry cough, tiredness and last but not least shortness of breath. Since high temperature is one of the prime symptoms [31] of this disease thermal imaging devices can be effectively used to detect the elevated temperature pattern in the human body. Numerous airports around the world [17] have installed thermal imaging cameras also referred to as heat scanners for the robust screening of the passengers. Further image processing and computer vision based algorithms are used to generate a color palette that represents different temperature scales that aids in the diagnosis of this virus. In the wake of widespread of COVID-19 virus, FLIR [18] is experiencing increased demand for its hand-held T-series products as well as its A310 fixed-mounted thermal imaging camera [19].

IV. Role of Image Processing and Machine Learning for Effective Human Thermography

Thermal waves are exponentially reduced in an environment, and hence the thermal effects of abnormalities are often subtle. Moreover, thermal images also suffer from a relatively low signal-to-noise ratio (SNR) [2]. Thus, digital image processing plays a vital role in providing reliable solution such that by applying a variety of filters in both frequency and time domain to overcome these factors [2, 32]. Digital image processing techniques are used offline to enhance the quality of low quality pre-recorded thermal images of the human body to better visualize the image from both human and machine perspective. It works by providing dynamic contrast control, edge preservation [2], and removing unwanted noise from the image by applying different algorithms such as applying various filtering methods, thresholding techniques and, probabilistic models. Once the images are refined, the enhnaced outputs of thermal imaginary datasets can be fed into a variety of machine learning algorithms to extract meaningful information which can ultimately help us to detect any type of abnormalities in the human body. Fig. 4 illustrates the generic comprehensive block diagram representation of a thermal imaging based Computer Aided Dignosis (CAD) system.

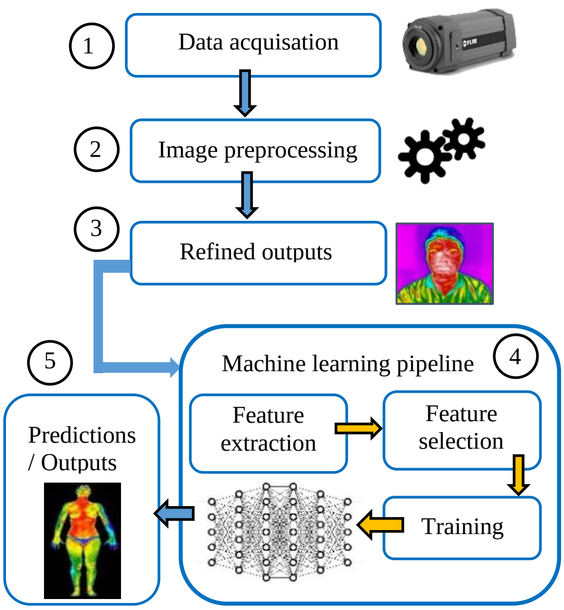

Fig. 4. Comprehensive block diagram representation of thermal imaging based Computer Aided Dignosis (CAD) system.

As illustrated in Fig. 4 the overall system works by acquiring images using different types of thermal cameras such as mobile thermal cameras, LWIR thermal cameras, and NIR thermal cameras. In the next step, the acquired data is processed using image processing algorithms to produce refined outputs. Refined outputs are then fed as input data in a variety of machine learning algorithms to extract important feature values. Conventional machine learning classifiers such as Support Vector Machines (SVM) and Naive Bayes mainly rely on handcrafted features that are engineered manually using a variety of feature extractors thus having chances of higher error rate. Also, the SVM classifier is not computationally efficient when dealing with large datasets. As a solution to this Deep Neural Networks (DNN) plays a prime role since it uses learned feature values that are self extracted from raw pixel images. Therefore, DNN benefits us by providing high accuracy and mitigating the drawbacks handcrafted feature engineering. DNN is extensively used for classification and segmentation applications in medical imaging to provide the second opinion to doctors and specialists. To train these networks, different types of network hyperparameters are used to achieve optimal generalization and regularization in DNN networks. It includes the selection of appropriate error function, optimizers, learning rate, momentum, batch size, and the number of iterations. Finally, the networks are trained to achieve precise and robust accuracy levels which are validated by performing cross-validation on unseen test data.

V. Proposed Methodology for Breast Cancer Classification using Deep Learning

In this section, we have proposed a breast tumor classification system using thermography images of breast cancer by applying deep learning methodologies as discussed in Section IV. It is the most common type of cancer throughout the world and found very commonly in women. In 2020 it is expected that about 276,480 new cases of invasive breast cancer are to be diagnosed in women only in the U.S along with 48,540 new cases of non-invasive (in situ) breast cancer [26]. However, if it is detected in preliminary stages it is treatable by taking suitable medical measures.

In our study, we have utilized DMR - Database for Mastology Research [21]. It is a type of online platform that stores and manages mastologic images for early detection of breast cancer. The dataset is consisting of different modalities of breast cancer images which include thermography images, mammography images, MRI images, and ultrasound images. The dataset was collected using FLIR SC-620 camera [22] from 287 patients of different age groups. The overall dataset includes images using static and dynamic data acquisition protocols. In static data acquisition set up the body of the patient must achieve thermal balance in a controlled environment whereas dynamic protocols are used to inspect the skin temperature recovery caused by thermal stress after cooling the patient by electric fan. For the proposed study we have used data acquired through the dynamic protocol as it provides extensive thermal data as compared to static data. Dynamic data acquisition provides a set of 20 images and 2 additional lateral images of each patient which was acquired during a certain interval of time. Considering the dynamic methodology, we have used data of 40 patients, among which 18 patients belong to the cancerous class and 22 patients belong to the healthy (benign) set. We have utilized a pre-trained Inception-v3 deep neural network [23] network for effective classification between benign and cancerous cases. Fig. 5 shows the complete workflow diagram of the proposed system.

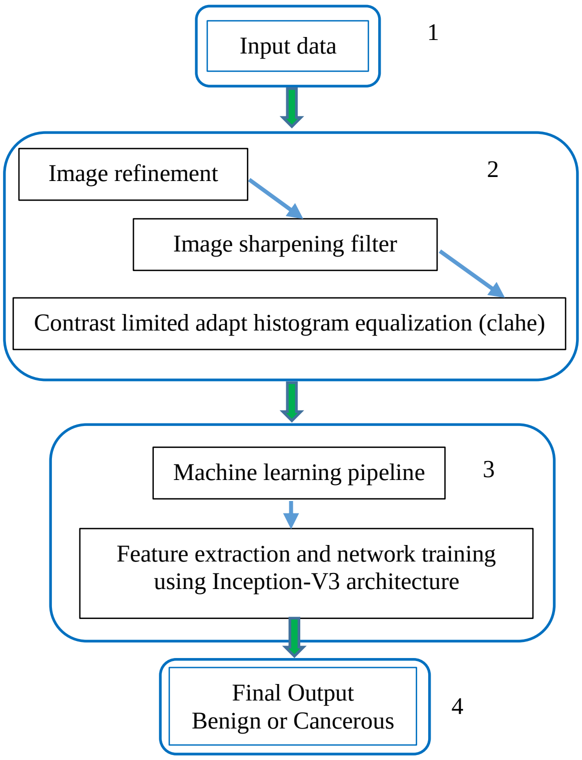

Fig. 5. Complete workflow diagram for autonomous breast cancer classification system.

A. Image Processing

As shown in Fig. 5, in the first phase system works by performing the image preprocessing operations which includes applying initial sharpening filter and then applying Contrast Limited Adapt Histogram Equalization (CLAHE) operations on original images provided in the dataset. The sharpening filter is used to increase the contrast in the images, especially where different color channels meet. CLAHE operation is used for performing intensity normalization in the image. It works by taking different parameters which include distribution and clip limit. Distribution specifies the spreading scale that histogram equalization will utilize as the basis for generating the contrast transform function. Clip limit is generally defined as an overall contrast enhancement threshold limit. We have used uniform distribution function that creates a flat histogram and clip limit is set to 0.01. The main purpose of applying the image preprocessing operation is to refine the existing image quality by making the high-level features more descriptive which will be further used for training the CNN network. The same preprocessing techniques are applied to whole training data. Fig. 6 shows the preprocessing operations applied to one of the test cases from DMR - Database for Mastology Research [21].

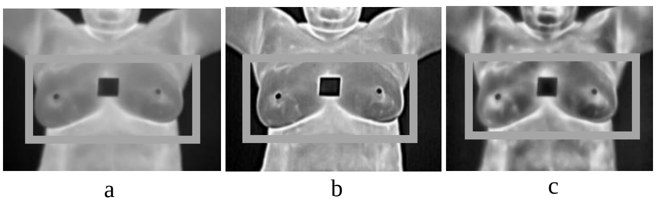

Fig. 6. Preprocessing operations applied on thermographic breast tumor image a) original image, b) sharpened image, c) contrast limited adapt histogram equalization image.

B. Deep Neural Network Training

In the second stage, the processed images along with original images are used for training the state-of-the-art inception-v3 [23] network. It is a 48-layer deep neural network designed by Google Brain which was initially trained on ImageNet library [24]. The main reason for employing this network, it uses multiple features from multiple filters which improve the overall performance of the network. Moreover, all the established architectures before the inception network performed convolution on the spatial and channel-wise domain together. By performing the 1x1 convolution, the inception block is doing cross-channel correlations, thus ignoring the spatial dimensions. It is then followed by cross-spatial and cross-channel correlations using the 3x3 and 5x5 filters. In the proposed study we have used the weights of the pre-trained inception -v3 network and retrained the last layers of the network for our custom breast tumor classification task by applying transfer learning.

VI. Experimental Results

The overall algorithm is implemented using Core I7 sixth-generation machine equipped with NVIDIA RTX 2080 Graphical Processing Unit (GPU) having 8GB of dedicated graphic memory. As discussed in Section V we have first applied image preprocessing operations to refine the original images provided in the dataset. The processed images along with original images (input image size of 299 x 299) are used for training the state-of-the-art inception-v3 [23] network using TensorFlow deep learning platform as exhibited in Fig. 7.

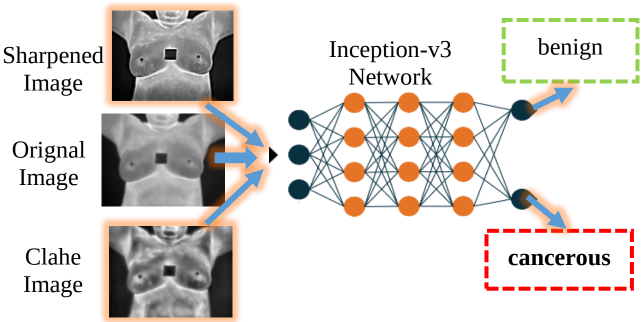

Fig. 7. Training of inception-v3 architecture for breast tumor classification.

The data is distributed in the ratio of 70%, 20% and 10% for training, validation, and testing purposes in an empirical fashion. After getting unsatisfactory training and validation experimental results in the initial stages, the following set of network hyperparameters is selected as shown in Table II to avoid model overfitting and achieve optimal generalization.

TABLE II. Inception-v3 Training Parameters

Epochs	Learning Rate	Batch size	Optimizer	Error function
5000	0.001	32	Stochastic Gradient Decent (SGD)	Binary Cross-Entropy

The system achieves the overall training accuracy of 93.73% and validation accuracy of 91.32%. Fig. 8 shows the accuracy and loss graph of the inception-v3 network.

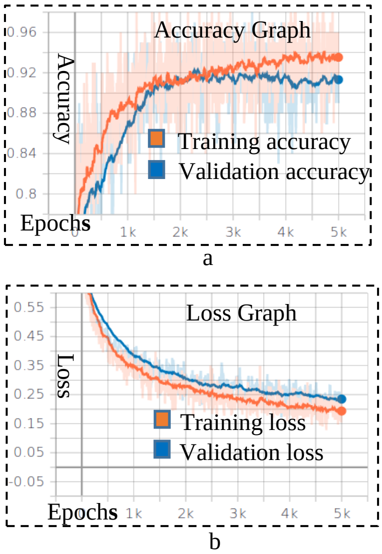

Fig. 8. Inception-v3 network training and loss graphs a) training and validation accuracy graph, b) loss graph of inception-v3 network.

The classifier is then cross-validated on unseen test cases to check the overall test accuracy of the network. It is important to mention that the trained network is tested without applying any of the preprocessing operations on test data to validate the overall robustness of inception-v3 architecture. Fig. 9 shows the results of the correct prediction on two random test cases along with the confidence scores and individual inference time required. The overall performance of the inception-v3 network on test data has been evaluated using five different quantitative measures which include accuracy, sensitivity, specificity, precision, and F1 score [25]. The results of these metrics are shown in Table III.

TABLE III. Quantitively Metrics Results

Metrics		Score
1.	Accuracy	80%
2.	Sensitivity /Recall	83.33%
3.	Specificity	77.77%
4.	Precision	71.43%
5.	F1 Score	76.89%

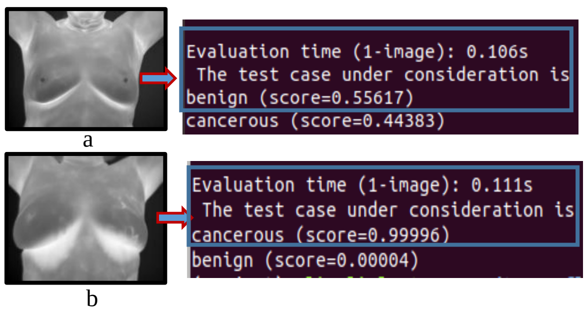

Fig. 9. Inference results on two random correct cases a) Patient 1 prediction: benign case with a confidence score of 55.61% and inference time 0.106 second, b) Patient 2 prediction: cancerous case with a confidence score of 99.99 % and inference time of 0.111 second.

VII. Conclusion and Future Work

The main objective of the entire study is to emphasize the importance of thermography and role of machine learning in thermal medical image analysis for human health monitoring and disease diagnosis in prodromal stages. Technologically advanced platforms for performing effective human thermography are also referred to as Computer-Aided Diagnosis System (CAD) and is considered to be a sixth sense and reliable second opinion for doctors, specialists and medical experts. This has been evident in our study by proposing a breast tumor classification system using grayscale thermal images. The system works by employing sate of art inception-v3 architecture for performing precise classification between benign and malignant (cancerous) cases. The system achieves the overall accuracy of 80% and the sensitivity of 83.33%.

For future prospects, we believe that extensive use of smartphone-based and commercial grade thermal cameras could make human thermographic data widely accessible for investigating in depth details in this area. Moreover, advanced computational techniques such as machine learning and deep learning algorithms can be integrated with existing thermal cameras hardware to come up with the concept of smart thermal diagnosis systems. Such types of systems can be deployed in cars for in-cabin Driver Monitoring Systems (DMS) for making correct predictions about the driver's health promptly.

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