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Breast Cancer Detection in Thermal Images Using GLRLM Algorithm

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***Abstract*—In recent years it has been noticed that early breast cancer detection can decrease death rates considerably and to pursue early detection, there is a need for advanced screening tool along with experts, among screening tools infrared camera in thermography is low cost, contactless and does not include vulnerable rays, so it can be a good alternative to the most common screening tool techniques like mammography which entails all of the mentioned limitations. This paper aims to introduce an architecture by which the computer automatically classifies the cases into the malignant, benign and normal using labeled Thermal breast images. To obtain our goal, Gray Level Run Length Matrix (*GLRLM*) algorithm for feature selection and Long Short-Term Memory (*LSTM*) as a classifier are utilized. We achieved near 100% accuracy result for the training process, and for testing, we are selecting eight trained images of a single patient and we get quite accurate outcome. This proposed method using thermal images is a completely non-invasive method for cancerous patients in comparison to other methods.**

Keywords— Breast Cancer Classification, GLRLM, Infrared Images, LSTM, Thermography.

I. INTRODUCTION

According to World Health Organization in 2020 the female breast cancer cases have the highest rate of worldwide cancer which previously was the place for lung cancer. Breast cancer also has the highest ranking of mortality among cancer cases in 110 countries this year, although in American Cancer Society, investigation shows since 2007 mortality of breast cancer rate constantly decreasing among aged women, thanks to early-stage recognition possibility (by utilizing advanced tools of screening), more women awareness and improved cure procedure by which treatments are more effective [1], [2].

Cancer happens when healthy cells in the body started to grow and divide in an uncontrolled way, and makes a mass of cells. Benign and Malignant are two types of tumors. Benign tissue mostly does not classify as cancer since it is not invasive and affected cells have undergone a negligible change. If the cancerous tumor is malignant, then it has the potential to grow and spread to other organs to invade.

Early detection using screening techniques for instance clinical breast examination (CBE) might be quite helpful for effective treatment, Computed Tomography (CT), CBE includes X-ray mammography, Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), Ultrasound (US), breast temperature measurement and histopathological image analysis. Artificial Intelligence (AI) is a promising tool that has shown breakthrough results for cancer detection. Computer-Aided Diagnosis (CAD) by the usage of novel machine learning methods will help in early stage cancer detection and classification of the cancer cells. In traditional screening methods, some drawbacks made patients not feel pleasant and sometimes they avoid undergoing these methods because most of them are invasive, use harmful rays and costly. Mammography is the main screening technique used for the efficient diagnosis of breast cancer at an early stage these days. The main disadvantage of mammography is that it uses X-Ray which is intensely detrimental, so an alternative screening technique should be considered. Thermal image analysis for breast cancer detection has gained fewer cancer researchers' attention while it excludes the raised issues and can be a good alternate[3].

A. Introduction to Thermal Screening for breast cancer

Human body temperature can be an actual indicator to detect some diseases. Recently, a wide range of research has been conducted to boost up the utilization of thermal cameras and to establish a strong connection between thermal physiology and temperature of skin [4]. Thermographic image utilizes the infrared method that is non-invasive, fast, contactless and flexible to monitor human body temperature. Nowadays not only Medical is using Thermal images to find the disease but also it is helping Biomedical researchers to advance the curing systems. In Thermography, information provided from breast images contains fundamental data on the temperature and condition of breast tissue vessels but it does not include the morphological structures of breast cancer. These fundamental data are thought of as a sign of initial structural changes that resulting from disease or cancers occur. Thermal imaging is low-cost and not harmful for humans, therefore it is an effective method, also to diagnose the type of tumor, there are researches are going on[5], [6].

B. Introduction to GLRLM algorithm

The texture is a set of gray level pixel matrices that contains information about the spatial discipline of intensities or color. Grey level run length matrix (GLRLM) which first time proposed by Galloway, is based on the second-order statistical analysis [7]. A set of pixels that include identical gray level values which successively and in the same direction have distributed in the region of interest (ROI) is called gray level run. The same number of pixels in the particular direction is known as the length of the gray level run. GLRLM is a 2D matrix from ROI consists of the gray level values run in the rows and the length of run values in the column, it simply divides the occurrence of total types of combinations of gray level run in a specific direction.

Values and run lengths of gray level are taken in the form of (*m,n*)-th entry in the matrix. Four main directions horizontal (0°), anti-diagonal (45°), vertical (90°) and diagonal (135°) are deliberating here. Table I shows a set of ROI pixels, GLRLMs of the corresponding table in different main directions are given in Table II. In Table I. three different pixel values are shown(N=3), hence the GLRLM would be a 3×3 table that denotes the different pixel values (N) and with a maximum of 3 run lengths.

TABLE I. A SPECIFIC ROI

0	0	128
255	128	0
255	0	128

TABLE II. GLRLM IN FOUR DIVERSE DIRECTION

Table2:GLRLM of Table1			
0° →			
V\L	***1***	***2***	***3***
0	2	1	0
128	3	0	0
255	2	0	0
45° ↙			
V\L	***1***	***2***	***3***
0	4	0	0
128	1	1	0
255	2	0	0
90° ↓			
V\L	***1***	***2***	***3***
0	4	0	0
128	3	0	0
255	0	1	0
135° ↘			
V\L	***1***	***2***	***3***
0	4	0	0
128	1	1	0
255	2	0	0

If we define GLRLM as S then $S_{m,n}$ would be the (m,n)-th entry with m rows and n columns matrix. Besides, K_r has been utilized to indicate the set of various run lengths that present in the ROI, and K_g depicts the different gray levels shown in the ROI. At the end total number of pixels K in the ROI can be reached as stated below:

$$K = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} nS_{m,n}$$

C. Problem Statement

In this work, we are introducing an advancement in the thermal breast cancer screening method. It is quite challenging to develop a breast cancer screening procedure that uses medical imaging while not being invasive and does not require physical interactions. Thermography can be used as an alternative for early breast cancer diagnosis and treatment. In this work an end-to-end architecture is proposed, first boundary-based segmentation is utilized to divide the breast thermal image into segmented parts, then GLRLM is performed on the parts of images to captures deep features [8]. In the end, a recurrent neural network (RNN) is applied to classify the image and obtain the final extracted result.

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II. RELATED WORK

N.Darabi et al. in their research [9] used Random Subset Feature Selection (RSFS) algorithm to select features then KNN and SVM classifiers have applied, the result represent the accuracies of 85.36% and 75% respectively, in this paper other methods such as minimum Redundancy Maximum Relevance and Genetic Algorithm are used as a hybrid method with RSFS but there are still hopes for increasing accuracy. In [10] C.Kumar et al. used thermal breast cancer screening tool which is based on AI (Thermalytix). They also used radiological findings along with Thermalytix to diagnose cancer as benign, malignant or normal. The authors conclude that thermalytix with radiological findings works well. R.Karthiga, et al in [11] proposed a novel method by applying the curvelet transform and a Gray-Level Co-Occurrence texture feature to thermal images then, classification is achieved by utilizing well-known machine learning classifier SVM, with 93.3% accuracy. S.T. Kakileti et al. in [12] searched about the cancer risk chances by using Thermalytix Risk Score (TRS) on breast thermal image patterns. In the obtained results, the TRS evaluated the breast cancer risk with a 0.89 AUC which was higher than the AUC of age-based Risk Score. R.Sánchez-Cauce et al. in [13]built an architecture that has multi inputs for classification that employs the advantage of CNN, they have used the publicly available database, Database for Mastology Research (DMR) with Infrared Image, also they achieved 97% accuracy in their work. All these applications have required larger computational time to conduct the parameter assessment, therefore there is a need for improvement in detection and accuracy of breast cancer using thermal screening. In our work, the solution for the betterment is provided using GLRLM algorithm to detect and localized malignant, benign and normal tumor.

III. Methodology

A. Motivation

It is vital to detect cancer in the early stage for better treatment. This will be achieved by the amount of enough experienced physician as well as advanced cancer screening system around the world which is rare in underdeveloped countries, taking help of an automatic cancer diagnosis system using thermal images is a remarkable way to reduce the limitations due to its low cost and non-invasive functionality, observing the advancement process of breast cancer contactless is another significant preference of women which can be fulfilled with thermal imaging process, also investigation during the years on AI techniques shows that accuracy achieved in machine learning can overcome the traditional detection system in cancer and reduce the human error.

B. Proposed Work

In this work, a technique is presented to classify and detect tumors within the breast. In breast cancer detection using CAD the algorithm for classification is the same as other artificial intelligence based systems and overall consists of preprocessing, then segmentation process, extraction and selection of features is the next step, and the last stage refers to classification [14]. The general stages of our proposed method are introduced in Fig. 1. The first step in this work is image acquisition, here the "Mastalogy" Thermal images are applied, then in the next stage, thermal images are preprocessed to make the Thermal images more visually enhanced because during acquisition, noise corrupt the image, further, we used boundary segmentation to localize salient boundaries, next GLRLM algorithm is applied for feature extraction and feature selection. In the last step, we used RNN classification to train and classify the testing set into malignant, benign, or normal. To elaborate on the proposed method this section is described in separated parts completely.

1) Image Acquisition

The proposed method is applied on a set of thermology images dataset called "Mastology".The resolution of images is 640 × 480 pixels and there are total 235 images.

Explanation of Dataset

In the proposed method, the dynamic thermograms dataset [15] is used to train and test. Database Mastologic Research (DMR) is available in (http://visual.ic.uff.br/dmi/). in order to obtain dataset initially, a cooling process is done to decrease the breast temperature to the range between 20ºC to 22 ºC, by exposing the patients to an electrical fan, then a FLIR camera (model SC620) was utilized to take 20 infrared images five minutes after decreasing body temperature.

Among the individuals taken pictures from, there were 47 cancerous patients and 184 normal persons. The dataset contains breast images with their respective thermal infrared parts but in the dataset, the lesion size, breast size and the density of breast has not mentioned.

2) Pre-processing

Thermal images have captured in a different condition so it contains noises and artifacts, at the beginning, to obtain the ROI we need to crop the images, further the adaptive median filter is employed to suppress the noise and artifact to make a better visible image for the later procedure.

3) Segmentation

In segmentation, the infrared colored parts get segmented from the background using boundary-based techniques like thresholding and gradient to detect obvious or circumstantial boundaries between regions for diverse tissue types.

4) Feature Extraction and Feature Selection

Feature Extraction has a significant functionality to detect and classify thermal images in our work, In this stage, a particular feature of interest inside a thermal image is chosen for next thermal image processing. Texture feature utilized to detect the regions affected with cancer in the thermal images. The texture is called a set of consecutive patterns that has a particular frequency. In order to produce texture models, Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM) are used. For extraction and selection of features from images, GLRLM algorithm is used to help health professionals to avoid false-positive prediction [16]. The GLRLM algorithm can simultaneously solve the issue of statistical computations in various overlapped ROIs on a thermal image in parallel primitives. After quantizing the lower bit levels and evaluating the GLRLM, the following eleven texture parameters are used:

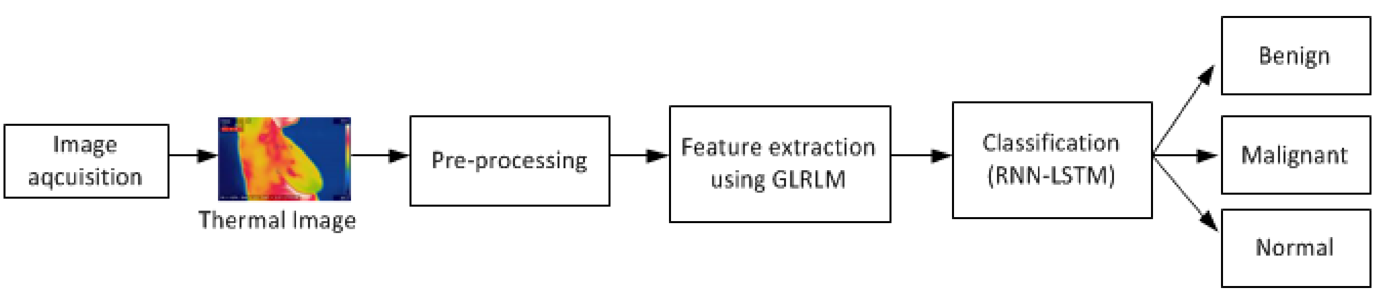

Fig. 1. Block diagram of the proposed Work

- Short Run Emphasis (SRE)

$$SRE = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} \frac{S_{m,n}}{n^2} / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

- Long Run Emphasis (LRE)

$$LRE = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} n^2 S_{mn} / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

- Gray Level Nonuniformity (GLN)

$$GLN = \sum_{m\epsilon K_g} \left(\sum_{n\epsilon K_r} S_{mn} \right)^2 / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

- Run Length Nonuniformity (RLN)

$$RLN = \sum_{n\epsilon K_r} \left(\sum_{m\epsilon K_g} S_{mn} \right)^2 / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

- Run Percentage

$$RP = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}/N$$

- Low Gray Level Run Emphasis ($LGRE$)

$$LGRE = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} \frac{S_{mn}}{m^2} / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

- High Gray Level Run Emphasis ($HGRE$)

$$HGRE = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} m^2 S_{mn} / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

- Short Run Low Gray Level Emphasis ($SRLGE$)

$$SRLGE = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} \frac{S_{mn}}{m^2 n^2} / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

- Short Run High Gray Level Emphasis ($SRHGE$)

$$SRHGE = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} \frac{m^2 S_{mn}}{n^2} / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

- Long Run Low Gray Level Emphasis ($LRLGE$)

$$SRHGE = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} \frac{n^2 S_{mn}}{m^2} / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

- Long Run High Gray Level Emphasis ($LRHGE$)

$$LRHGE = \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} n^2 m^2 S_{mn} / \sum_{m\epsilon K_g} \sum_{n\epsilon K_r} S_{mn}$$

It is understandable that symmetrical feature in gray levels shows by m and run length indicates by n. The SRE and LRE are potentially worthy in classification. [8]

5)Classification

After selecting features in the images, they are applied as an input to the classifier in order to obtain multi-class classification of normal, benign or malignant labels. Training neural network is done by adjusting the weights and predicting the correct class. For classification recurrent neural network (RNN) is used and long short term memory (LSTM) has chosen to avoid vanishing gradient or long term dependencies issues. Padding is done as a mask on the image for a better result in batch normalization. Fig. 2. shows an LSTM that takes the previous output result as the new input.

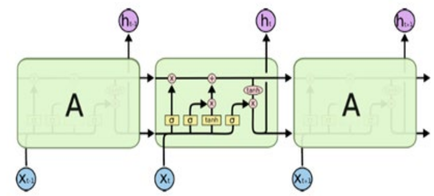

Fig. 2. basic architecture of LSTM

LSTM is utilized to train the temporal data, and for sequence images LSTM known as preferable choice, it is considered as a lightweight model with long term dependency if it compares to Convolutional Neural Network, also it takes less computational time [17].

RESULT AND DISCUSSION

In the proposed method a total of 235 cancerous patients have been chosen for the work. First the images are preprocessed and they are segmented using boundary segmentation, during padding. The preprocessed images are used for texture features extraction based on GLRLM, In table III. the values of extracted features for malignant, benign and normal images are given respectively.

Table III. Feature extraction Result

Feature	Malignant	Benign	Normal
SRE	4.22	4.7765	3.53
LRE	94.5	51.5975	100.89
GLN	1.73e+04	2.4195e+04	1.0977e+04
RP	32.29	41.6201	25.20
RLN	8.32E+04	1.3378e+05	4.7759e+04
LGRE	0.9396	1.4544	0.5937
HGRE	694.7926	427.5538	671.1850
SRLGE	7.989	29.6271	26.6791
SRHGE	9.0827	3.3947	0.9026
LRLGE	7.989	0.0015	26.67
LRHGE	1.8214e+05	1.4104e+05	1.8214e+05

From every patient, 8 different thermal images from diverse positions have been selected as can be seen in Fig. 3.

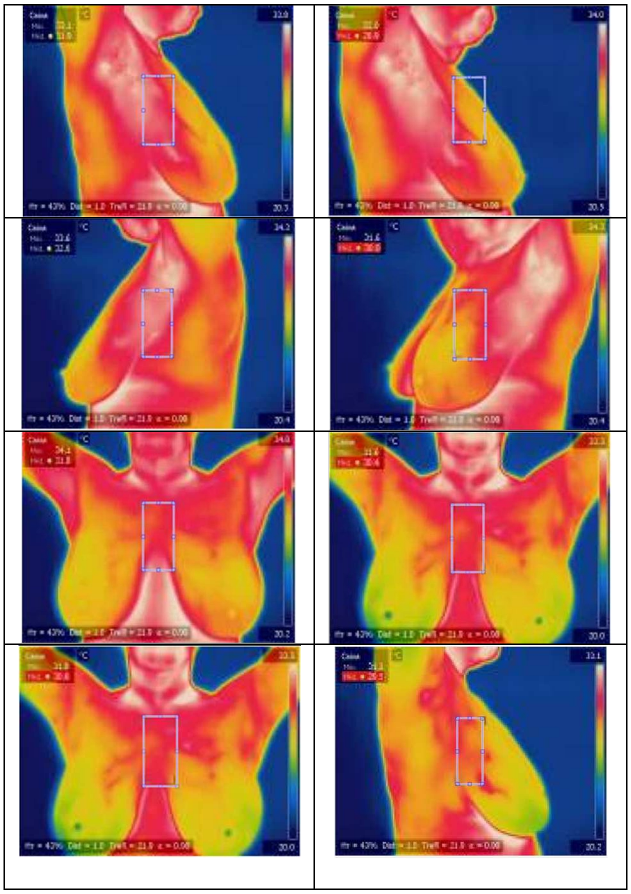

Fig. 3 . Thermal image for breast captured from different angles

Then we split the data into training and testing separate sets with the ratios of 70% and 30% in order, after that we use it as an input to the LSTM classifier. The result depicted that this architecture could differentiate malignant, benign or normal masses with accuracy more than 99% in the training process Fig.5., and gives a quite accurate differentiation in testing set as well , it has shown in Fig.4.

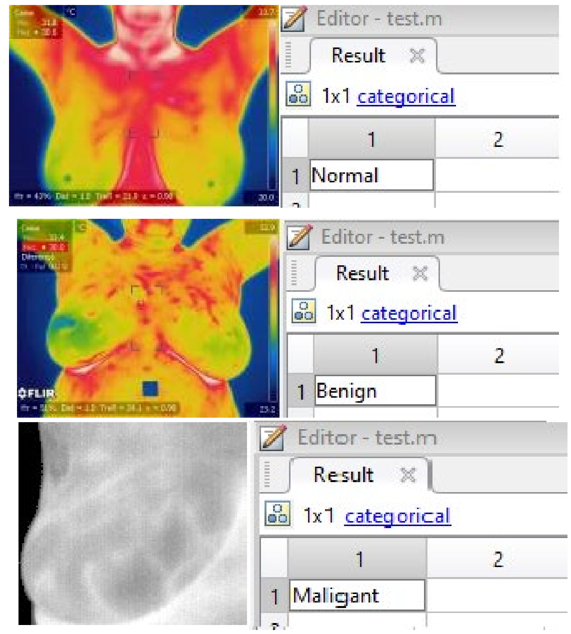

Fig. 4. shows the testing result for a (Up) Normal patient, (Middle)benign patient and (Down) malignant person images

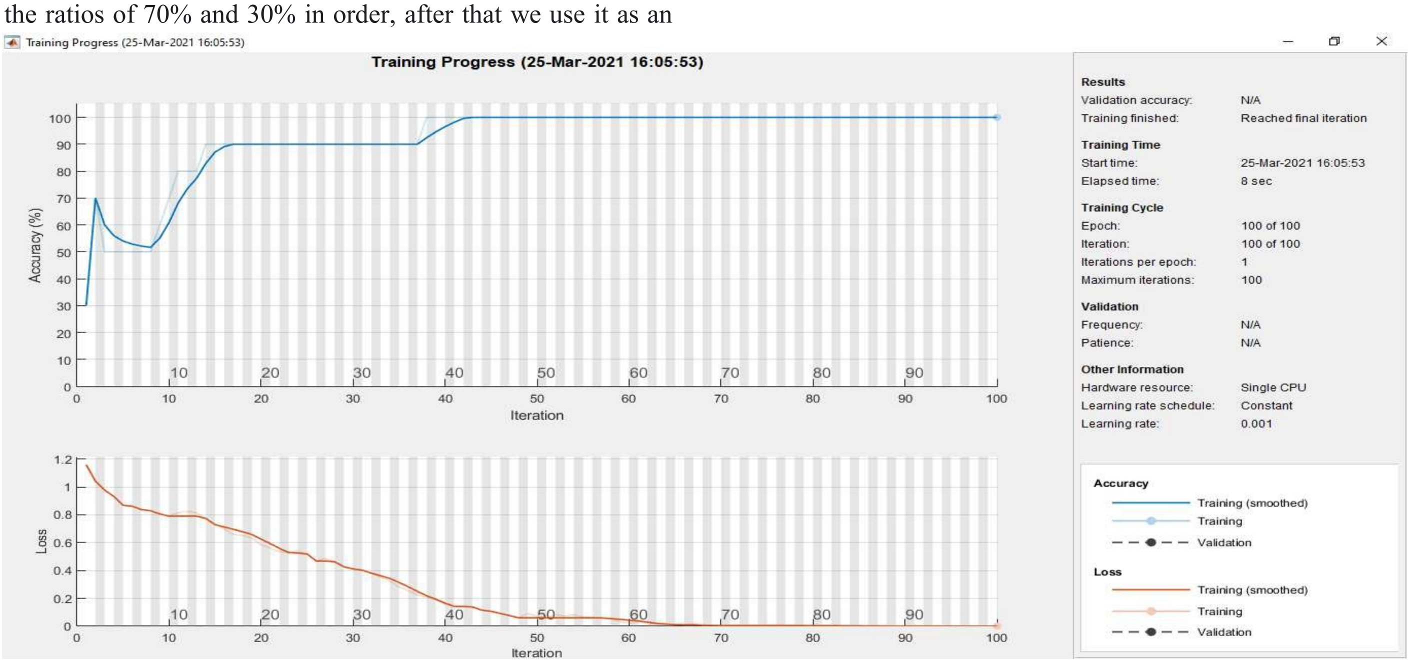

Fig. 5. Accuracy and Loss for the taring process

IV. Conclusion

In this work a new approach is proposed to detect the type of cancer from thermal images. “Mastology” images are utilized as the dataset, and after preprocessing, enhancement and segmentation, GLRLM is applied for the feature selection and finally images are used as inputs for the well-known LSTM classifier to train the training set and classify the testing set, the proposed work obtained near 100% accuracy in training and almost complete correct prediction in testing set. Thermal image processing for cancer detection in this method is a non-invasive technique in comparison to other common methods also it is less costly and worth to employ more for researches in cancer detection.

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