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Fourier analysis for Skin lesions diagnosis

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ABSTRACT:--

Skin cancer is the deadly disease that is difficult to identify and diagnose. Detection of such harmful part is a difficult task. In this paper a mathematical framework is developed base on the appearance of the image and the gray levels. Identification and nature of the image pixels is evolved by calculating respective Fourier components and magnitude values. The identified values are helpful to understand the nature of the benign skin and malignant skin. The parameters calculated are PSNR, SSIM, and Maximum value in the image. Mathematical modeling is a promising approach to reveal disease-related regulatory mechanisms To uncover regulatory processes associated with diseases, mathematical modelling is an encouraging strategy. This work provides a synopsis of the advantages and disadvantages of mathematical modelling in its application to the study of skin disease. The study covers skin kinds, lesion types, several mathematical methodologies, and the visual look of the picture, all while considering the skin's behaviour at different intensity levels. A mathematical model using fast Fourier transform, lesions, SSIM, and PSNR is used. Keywords;- FFT, Mathematical Model, PSNR, SSIM

I. *INTRODUCTION*

According to reports, skin cancer is among the most common types of cancer, particularly among persons of Caucasian descent and those with light skin. Among the three most common types of skin cancer, melanoma is statistically the deadliest. It is also the fifth most common cancer in men, the seventh most common cancer in women, and the second most common cancer in people aged 15 to 29. There is an urgent need to address these problems by using developments in telecommunications-based services to give medical diagnoses under extremely constrained time frames. Additionally, this programme has been designed to decrease needless biopsies, speed up the diagnostic process, and provide reproducible findings.

A. HUMAN SKIN

Complex geometry and local optical qualities characterize the surface of human

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skin, which is a detailed landscape. In humans, the biggest organ is the skin, which is composed of three main layers: the epidermis (2.1), the dermis (2.2), and the subcutaneous (2.3). A number of critical factors, including the subject's age and gender, the imaging settings (lighting or camera), the direction of illumination, and the body's position (forehead or cheek), significantly impact skin characteristics. Automated medical image processing is hindered when bacterial and viral skin diseases decolorize and distort pigmented skin patches [1].

i.Pores

The outermost layer of skin, the epidermis, provides a protective barrier against harmful environmental factors, including harmful radiation, wounds, and contaminants. Four cell types—Keratinocytes, Melanocytes, Langerhans, and Merkel cells—make up the epidermis.

ii. Hypodermis

Collagen and elastic fibres make up the dermis. The dermis consists of two main layers: the dermis and the reticular dermis, which are substantial layers that provide nourishment and energy to the epidermis, and the papillary dermis, a thin layer that adheres to the epidermis. Wounds, hair follicles, lymphatic veins, sweat glands, and nerve endings are all located there. It also controls our sensation of touch and the healing process.

iii. Subcutis

The remaining two layers get their nutrition from the subcutaneous layer. The subcutis provides insulation and cushioning as a result of its composition of adipose and connective tissue.

B. SKIN LESION TYPES AND THEIR CHARACTERISTICS

Machine interpretation of images, usually presented in a way that might promote efficient decision-making, is the main goal of image analysis, which employs image processing methods. Contrary to popular belief, medical imaging is still not accessible to three quarters of the global population, according to a World Health Organisation (WHO) report [2]. This is despite the fact that medical imaging is becoming increasingly important in the era of telemedicine, particularly in the automation of skin disease diagnosis. So far, medical imaging has been a huge help in developing better medical practises. One major obstacle, however, is that underserved and underdeveloped areas still rely significantly on medical specialists whose availability is poor or nonexistent when it comes to interpreting and analysing medical imaging findings (particularly in rural settings).

Segmenting a mole, which gives crucial output for mole feature extraction and mole classification, is the primary duty of medical skin imaging. The localised multiplication of pigment cells (melanocytes) is the basic cause of moles, which are skin lesions. Melanocytic nevus (naevus) is another name for this condition since it develops from melanocytes. A mole may usually be either born with it or developed over time. Some areas consider congenital melanocytic nevi to be birthmarks since they are present from birth. Size is a common criterion for categorising congenital moles. There are three primary sizes of congenital moles: tiny, medium, and large (garment). Unprotected sun exposure, immune system, heredity, and, in rare cases, medication-induced unanticipated side effects are among the many causes of acquired melanocytic nevi, which often manifest in later childhood or adulthood [3]. Age is associated with an increased risk of mole conversion from nevi to cutaneous melanoma, particularly in cases of dysplastic nevi [4, 5]. In guys less than 20 years old, 1 in 2,000 may get a benign mole that becomes visible on the skin, whereas in males older than 40 years old, 1 in 33,000 may experience the same thing [4].

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Although the majority of moles in teenagers won't develop into cutaneous melanoma, warning signs should be considered when scheduling exams for worrisome moles [4, 6]. This is due to the fact that some malignant melanoma might appear clinically as benign lesions [6, 7].

The presence or absence of melanin, blood, or external pigmentation determines whether a skin lesion is pigmented or non- pigmented. Some Pigmented Skin Lesions (PSL) have been shown to be non- melanocytic, however the majority of PSLs are melanocytic (either benign moles or malignant) [8, 9]. You might say that the vast majority of moles are harmless. Malignant (threatening one's life) describes a cancerous mole. According to certain instances, benign nevi may develop into malignant melanomas [4, 10].

Melanocytic nevi are often categorised pathologically according to the skin location reference of the nevi cells. The nevus cells that cause a nevus to form might be found in the dermis or deeper layers of the skin. A flat mole connected to nevus cells at the epidermis-dermis junction is called a junctional nevus. Nevi in compound nevi are present both in the dermis and at the epidermo-dermal junction. Classification based on pigment patterns was developed by the use of dermoscopy in dermatoscopy. A starburst nevus appears as radial lines around the skin lesion's edge. Blue nevi are steel-blue skin lesions that are homogeneous in hue but lack structure. Besides spitz nevi, other frequent types of nevi include globular, dysplastic (atypical), lentiginous, cockade, and reticular nevi.

i. Different kinds of skin growths

Different types of sunshine cause different skin changes in different age groups. Freckles and moles are common skin markings that most individuals will experience at some point in their lives. Benign signifies that they are not malignant.

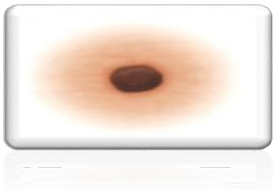
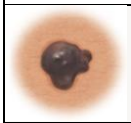
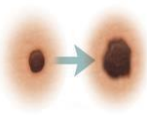


Fig1. Shows the Normal Mole on a skin

ii. Distinguishing benign moles from melanoma

There is an increased likelihood that certain moles may progress to malignant melanoma, a kind of skin cancer. Atypical moles and moles present at birth are more likely to develop into malignancy. It is crucial to detect skin cancers at an early stage since that is when therapy has the best chance of being successful. In order to detect the first signs of mole alterations, use the ABCDE chart that is provided below. Here are some of the warning signs:

Table 2. Shows the characteristics of various types of skin disorders

Melanoma	Sign	Characteristic
	Asymmetry	When half of the mole does not match the other half
	Border	When the border (edges) of the mole are ragged or irregular
	Color	When the color of the mole varies throughout
	Diameter	If the mole's diameter is larger than a pencil's eraser
	Evolving	Changes in the way the mole looks over time

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The image's nature may be deduced from the measurements of the traits and qualities listed in the following table.

Table 3. Essential features.

Features	Properties
Asymmetry	asymmetry index
	circularity factor
	skewness
Border irregularity	edge abruptness
	lesion areas and perimeters
	radial distance
	bounding box
	mean and variance of lesion boundary magnitude
Border Sharpness	compactness index
	fractal dimension
Colour	colour homogeneity
	island of colour
	colour histogram
	RBG statistics (such as ratio, chromaticity, spectral)
Diameter	lesion diameter
Differential Structures	pigmented network (typical/atypical)
	homogeneous areas
	branched streaks globules
	structure-less areas (such as dots, globules, blotches)
	blue-white veil
Lesion Surface Structures	co-occurrence texture features
	wavelet texture features
Other features	correlation index between geometry and photometry
	sonography characteristics, hypo-echogenicity

II. Literature Review

Skin texture analysis is frequently employed to segment lesions related to melanoma and dermatology. Nevertheless, eczema lesions are seen to have a less distinct border between the skin and lesions than melanoma lesions. This complicates the process of categorizing skin lesions caused by eczema. A review of the literature found that no research has been done to develop an automated, non-invasive, objective approach for rating the severity and extent of eczema. Digital imaging techniques were employed by Mathias et al. [6] to evaluate the severity of eczema, and the resulting score was associated with the EASI. With this approach, a camera is used to take digital pictures of the patients, which are then inspected by doctors who are not specialists in dermatology but have been trained in scoring systems. Using this procedure, establishing the score takes roughly thirty minutes. A histogram-based Bayesian classifier for erythema segmentation has been proposed by Lu et al. SVM is used to classify erythema zones according to severity [7]. An further study examines the characteristics and texture features of the Gray Level Co-occurrence Matrix (GLCM) in order to identify urticaria, dermatitis, and eczema [8]. In comparison to RGB, HSV, and YCbCr color spaces, a different study indicates that the CMYK color model provides good skin identification accuracy [9]. When employing the K-means approach for segmentation, various color models such as RGB, HSI, CMY, YCbCr, and CIELab are compared; the Hue channel has the highest lesion detection accuracy at 76.63% [10]. Color, texture, and SVM as a classifier are used in [11] to detect and quantify hand eczema. The front side of the hand had an F1 score of 58.6%, while the back side received a score of 43.8%.

A novel method for accurately identifying

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and categorizing skin lesions in order to diagnose melanoma is presented by the authors in [26]. The Partial Differential Equation (PDE) is used to split an image into two halves in order to detect skin lesions. In order to have an appropriate segmentation of the image lesion, the first component that adequately preserves the contour is thus utilized, while the second component offers a good characterisation of the texture. Additionally, novel and potent features derived from the skeletonization of the lesion are presented in order to increase the classification accuracy. Known features from the literature are merged and compared with these features. To choose the most pertinent traits to be kept for the classification stage, features engineering was used.

Within [27] The need for autonomous algorithms in medical imaging is growing, and as a result, quick models are needed to complete tasks like segmentation and classification. Nevertheless, the use of these models is highly dependent on the picture quality of datasets. Notable advancements in improving datasets for effective image analysis have been observed previously. Furthermore, machine learning and deep learning are widely used in this industry. Even with the introduction of these sophisticated methods, there is still a great deal of need for additional study. Preprocessing approaches have a wide range of applications in segmentation problems, according to recent research. One preprocessing method for enhancing a region of interest is contrast stretching. We suggest DE-ABC, a new hybrid meta- heuristic preprocessor that maximizes the contrast-enhancement transformation function's decision variables.

III. MATHEMATICAL FRAMEWORK OF SKIN LESION USING FAST FOURIER TRANSFORM:

In image processing, column (x), row (y), and z (value) are the most popular ways to describe pixel location in the spatial domain. However, there are situations when image processing operations in the spatial domain may be sluggish or ineffective, necessitating a transition to a different domain that provides compression advantages.

The conversion from the spatial to the frequency (or Fourier) domain is a frequent transformation. Many image filters that are used to eliminate noise, sharpen an image, examine recurring patterns, or extract features are based on the frequency domain. The x- and y-frequencies of a pixel indicate its location in the frequency domain, while the amplitude indicates its value. An image can be transformed between the spatial and frequency domains using the Fast Fourier Transform (FFT). The FFT approach maintains all of the original data, in contrast to other domains like Hough and Radon. Furthermore, unlike time-frequency or wavelet transforms, FFT fully converts images into the frequency domain. The FFT breaks down an image into sines and cosines with different phases and amplitudes, allowing repeated patterns to be seen.

Since they define the general shape or pattern of the image, low frequencies, which indicate gradual variations in the image, carry the most information. Abrupt fluctuations in the image are correlated with high frequencies; although they add more detail, they also carry more noise. Masking off background noise is one method of doing so.

A high peak in the center of the data often represents the lowest frequencies when a forward FFT is used to convert a picture from the spatial to the frequency domain.

There is significant variation in the values ranging from the low-frequency peak to the high-frequency noise, indicating the presence of background noise in the image.

Smaller peaks that include noise and high- frequency information encircle the core peak.

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A surface of the power spectrum, or the absolute value squared of the transform, can be shown for an alternative viewpoint. Next, maintain the surface's form while displaying positive power spectrum values using a base-10 logarithmic scale.

The power spectrum's surface representation aids in figuring out the threshold required to eliminate noise from the picture. To get a cleaner image, you could then compute an inverse FFT and create a mask to filter out the noise.

Discrete Fourier Transform (DFT)

The DFT for an image is given as:

$$F[k,l]=\frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}f[m,n]e^{-j2\pi\left(\frac{k}{M}m+\frac{l}{N}n\right)} \quad (1)$$

Inverse DFT is given as;

$$f[m,n]=\sum_{k=0}^{M-1}\sum_{l=0}^{N-1}F[k,l]e^{j2\pi\left(\frac{k}{M}m+\frac{l}{N}n\right)} \quad (2)$$

PSNR is most easily defined via the mean squared error (*MSE*). Given a noise- free $m\times n$ monochrome image I and its noisy approximation K, *MSE* is defined as

$$MSE=\frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N}$$

$$PSNR=10\log_{10}\left(\frac{R^2}{MSE}\right) \quad (3)$$

IV. Results:

Some of the results showing the appearance and study of the nature of the skin lesions and normal skin images.

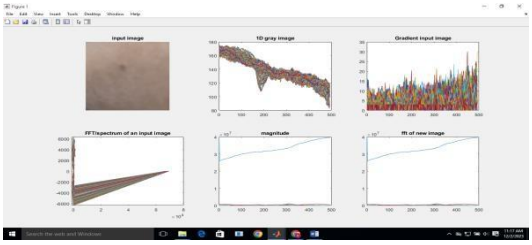


Fig 2. The normal skin image (Benign), its corresponding FFT and magnitude

V. CONCLUSION

Further phases of skin lesion identification and classifications may benefit from the mathematical models and representations

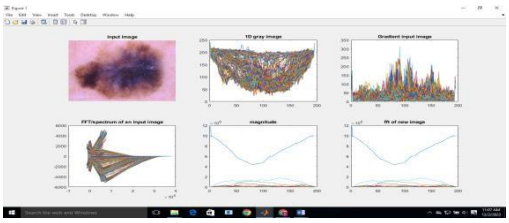
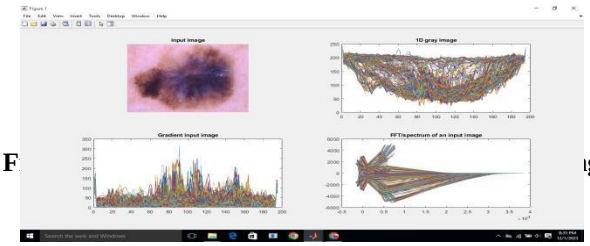


Fig 3. The skin image (Malignant), its corresponding FFT and magnitude representations



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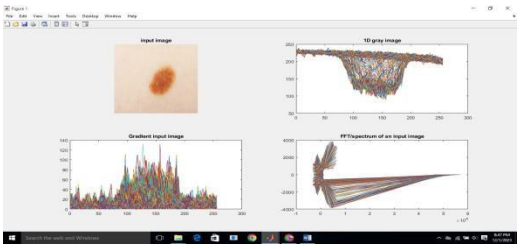

Fig 5. The skin image (Malignant), its corresponding FFT and magnitude representations

presented in this study. An essentially uniform magnitude characterises a normal skin picture, which, according to the representations, is analogous to a uniform probability distribution. Additionally, it is noted that the tumour picture follows a normal distribution in terms of size, whereas a small number of skin lesions with irregular borders exhibit nonlinear patterns. Noise, including masking structures, biological shape and tissue variability, and imaging system anisotropy, has been seen to impede the development of automated systems that may aid clinicians with medical imaging duties. These background sounds make it difficult to automate the process of analysing both micro and macro photos. We went over several methods that have been suggested in the literature to address some of the concerns raised by automated dermatological and clinical image diagnosis.Malignant moles are often

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assumed to be pigmented in most publications found in the literature. Be cautious, nevertheless, since there have been more and more cases of non- pigmented skin tumours and featureless moles being misdiagnosed during dermoscopy screening and clinical evaluation, respectively.

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