Innovations

Application of Texture Analysis Techniques and Image Statistics to Fund us Images for Effective Comparison and Analysis

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Abstract

The qualitative and quantitative image statistics plays a crucial role in medical image analysis. The data can be extracted using the machine learning techniques, containing the maximum information of the image based on their distinctive contrast, texture, or intensity fluctuations, tumors, lesions, or other pathological diseases can be recognised statistically. The term "image statistics" refers to the numerical measurements and traits that are employed to characterize the qualities and arrangement of pixel values inside an image. In this work, different texture analyses are applied and verified for the effective analysis of medical images. By using advanced applications we can even extract the data more efficiently.

Key Words: *Image Statics, Texture Analysis, Machine Learning, Medical Imaging.*

Introduction

Understanding and analyzing images relies heavily on image statistics. They offer numerical measurements that define different aspects of an image, enabling us to gather useful knowledge and make defensible choices[1,2]. Image statistics play a variety of roles that change depending on the application. They may be applied to tasks including object identification, anomaly detection, image enhancement, image segmentation, and quality evaluation. In a variety of disciplines, including computer vision, image processing, medical imaging, and more, academics and practitioners may learn about the features of images, identify anomalies, create algorithms, and arrive at well-informed conclusions by analyzing image statistics[3,4,5]. By identifying anomalies and distinguishing between healthy and sick tissues, image statistics support the identification and diagnosis of illness. Based on their distinctive look, texture, or intensity fluctuations, tumors, lesions, or other pathological diseases can be recognised statistically[6]. The process of obtaining important insights and data from digital photos is known as image analysis[7,8,9]. It includes a broad range of methods and algorithms for examining different facets of an image[10]. The factors taken into account during image analysis rely on the particular objectives and specifications of the study. Image resolution, color empty spaces, transparency, contrast, and sharpness are typical criteria[11,12]. Measurements can also be made of attributes including texture, form, size, and orientation. Other factors might include object detection and tracking, item identification and classification based on visual traits, or image segmentation to identify different regions of interest[13]. Image data is a term for visual data that describes how an image's visual information is represented digitally[14,15]. The colors, illumination, or arrangement in space or the visual elements included inside an image are encoded using a set of pixel values[16]. A pixel is a very small unit of information that holds a particular color or intensity value[17,18,19]. Each pixel may include one or more color channels depending on the color scheme of the image[20]. Digital images utilized in a variety of fields, such as imaging, machine vision, imaging in medicine, and graphic design, are built on image data[21]. Image data is now widely available, simple to share, and flexible to use with a variety of software and applications thanks to the development of modern cameras and image sensors[22]. The term "image statistics" refers to the numerical measurements and traits that are employed to characterize the qualities and arrangement of pixel values inside an image[23,24,25]. These figures offer insightful data about the image content, facilitating a better comprehension and examination of the visual information[26,27]. The histogram, minimum, maximum, mean, and standard deviation are all examples of common image statistics[28,29]. The median denotes the midpoint of the pixel distribution, whereas the mean denotes the average pixel value[30]. In order to determine the contrast and variance of an image, standard deviation calculates the scatter of the value of pixels around the mean. An image's variability in pixel intensities is indicated by the minimum and highest values[31,32]. A histogram, which depicts the frequency pattern of pixel values, may be used to spot strong tones and potential problems like excess exposure or underexposure[33]. Images are enhanced, segmented, objects are detected, and patterns are recognised with the help of image statistics, which are crucial to image processing, computer vision, and numerous analytical activities[34]. One may comprehend the whole dynamic range of the pixel intensity present by being aware of the least and highest possible values in an image[35]. This knowledge is helpful for a variety of imaging processing tasks, such contrast modification, whereby the pixel values may be adjusted to improve visibility or draw attention to certain aspects in the image. The image's lowest and maximum values can also be used to check for improper exposure, since exceptionally low or high values could signify underexposed or overexposed areas, respectively[36]. In various image analysis programmes, where particular characteristics or entities can potentially be identified by assessing their intensity levels within the image, determining the variety of pixel intensities are additionally essential[37,38,39,40].

Methodology

By giving quantitative data on the scope and location of abnormalities, image statistics aid in therapy planning. They aid in choosing appropriate treatment plans, which might involve radiation therapy or surgical procedures. Additionally, the efficacy of therapies may be evaluated through observation of modifications to image statistics over time. Images are improved and restored using approaches that are guided by image statistics. Image enhancement algorithms can manipulate the hue, saturation, and noise levels to better visualize and make correct diagnoses easier by analyzing statistical features like the median, standard deviation, and histogram. For quantitative evaluation, illness proof of identity, planning therapy, machine learning evaluation, images authentication, quality of images assessment, study findings, and clinical investigations, image statistics are crucial in medical imaging. They offer accurate measurements, improve image interpretation, and aid in the use of evidence when making healthcare decisions. Anomaly detection heavily relies on image statistics. Anomalies can be defined as departures from established statistical models or normative behavioral norms. This is advantageous in applications like medical imaging, where aberrant tissues or lesions may be found based on statistical differences from healthy tissues. Image statistics are

frequently used to rate the quality of images. A statistical analysis of factors like the amount of noise, sharpness, or contrast can be used to gauge an image's quality. This is crucial in industries including medical imaging, where the accuracy of a diagnosis is closely correlated with image quality. Reduces human subjectivity and mistakes while enabling precise and objective measurements. Enables decision-making by providing quantitative statistics along with conclusions from visual information. Saves time and money by facilitating automation and efficiency across numerous sectors. Aids in illness detection and diagnosis using medical imaging, enhancing patient care.
improves quality control procedures by identifying flaws and guaranteeing product uniformity.
Helps with object tracking and recognition, which enhances privacy and monitoring systems.
Allows for the use of remote sensing in urban planning, disaster management, and environmental monitoring. Allows for a thorough investigation of tiny and macroscopic images, which supports scientific research. drives the development of augmented reality and computer vision technology. Enables the relevant information to be extracted from the visual data, opening up fresh perspectives and discoveries

Standard measures are used to analyze and quantify specific aspects of an image using these values. Contrast is a measure of the variation in luminosity or color between different parts of the image, with higher values indicating more contrast. Dissimilarity measures the differences between neighboring pixels and represents the variety of textural elements present in the image. Greater variation is indicated by lower values, whereas homogeneity assesses the similarity or uniformity of neighboring pixels. More complex or textured images are indicated by higher numbers. The amount of information or overall complexity that makes up the image is represented by energy. The correlation between different pixel pairs in the image shows how linearly dependent they are on one another, with values closer to 1 showing a strong correlation.

Image contrast is the distinction in brightness and color between an image's brightest and darkest areas. It is essential for improving an image's visual impact and clarity. A high contrast photograph has clear, crisp edges and a strong feeling of depth, which makes the subject stand out clearly. On the other side, a low contrast image lacks visual appeal and seems flat since there is less tone distinction. Graphic designers and skilled photographers frequently utilize contrast changes to produce visually appealing images that focus the viewer's attention to certain details and add drama and emotion. A boring landscape may be turned into a riveting piece of art by striking just the perfect amount of contrast, which increases its impact and leaves an enduring memory.

Image dissimilarity is a measurement of how differently two or more photographs are from one another. To analyze and characterize the differences between images, it is a fundamental idea within computational imaging and computer vision. Image dissimilarity is calculated using a variety of methodologies, including pixel-based comparisons, feature extraction, and advanced learning algorithms. In order to perform tasks like image retrieval, object identification, and image comparison, it is important to be able to determine the degree of image dissimilarity. Researchers and practitioners may learn more about the differences and similarities of images by quantifying dissimilarity, which can help with a variety of statistical image analysis techniques and identification of patterns tasks.

image homogeneity, commonly referred to as uniformity, is the measurement of consistency or uniformity in an image. It measures how consistent or comparable individual pixel intensities are across an image's immediate neighborhood. A neighborhood with comparable pixel intensities has an appearance that is smoother and more uniform, which is indicated by a high homogeneity rating. In contrast, a place with a low homogeneity index is likely to be more diversified and textured. This idea is frequently applied during texture analysis and extraction of features activities to assist distinguish between various areas of an image with distinctive textures. Understanding image homogeneity is essential in many areas, notably medical imaging, where it helps to spot abnormalities or regions of interest with distinctive textural characteristics.

The degree of intensity fluctuation or "action" in an image is measured by image energy, which is frequently referred to as the quadratic sum or the magnitude of image gradients. It measures the degree to which local pixel intensities fluctuate from one location to another. High energy values reflect the corners, edges, or other intricate features in the image and are corresponding to regions with quick and large fluctuations in intensity. Low energy levels, on the other hand, signify areas with more consistent and rounded pixel fluctuations. It is common practice to employ image energy for edge identification, image segmentation, and removal of features tasks, where locating regions with notable intensity change is essential for further investigation and comprehension of the image's content.

The degree of resemblance or association between two photographs is measured by image correlation. It entails evaluating the connection between the relevant values of pixels in both images by comparing them. The pixel values at the respective places closely match when the correlation value is high, indicating substantial resemblance. A poor correlation, on the other hand, denotes image dissimilarity. Image correlation is used to align images from multiple sources or collected at various periods during different image processing jobs, such as image registration. Additionally, it is crucial for image compression approaches since it enables more effective data encoding and compression strategies by allowing for the identification of associated image areas. Overall, image correlation is essential for tasks involving image matching, alignment, and similarity evaluation in a variety of statistical image analysis and computer vision applications.

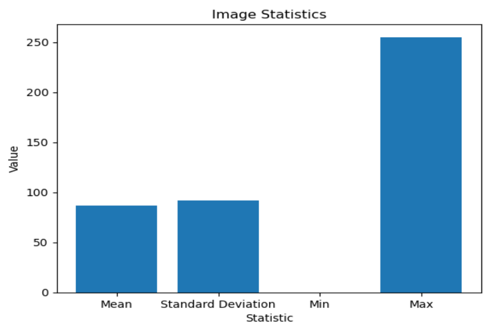
Results and Analysis

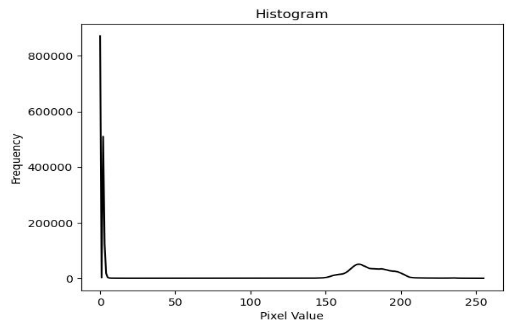
In this work, the techniques and methodologies are applied to the medical images to show and differentiate variations statistically using histogram graph based on the pixel value and bar graphs with min, max, and standard deviations of the medical images for better analysis and visualization. Texture analysis of the applied medical images is also calculated for further analysis.

Table : Texture analysis of different fundus samples.

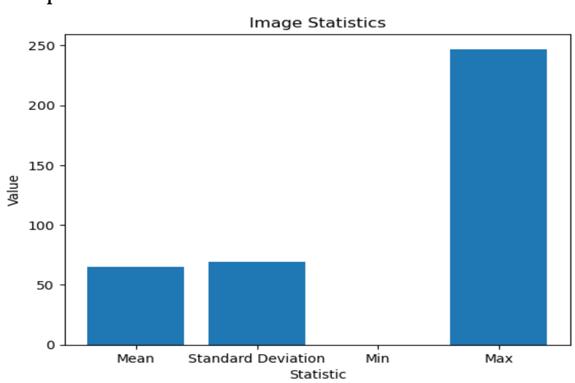
SNO	Contrast	Dissimilarity	Homogeneity	Energy	Correlation
Sample 1	6.6345	0.6609	0.7802	0.3308	0.9995
Sample 2	5.3281	0.8504	0.7257	0.3405	0.9994
Sample 3	4.5693	0.7144	0.7551	0.3398	0.9995
Sample 4	56.3711	4.6933	0.3350	0.1423	0.9688
Sample 5	13.9320	2.4261	0.3706	0.0422	0.9969

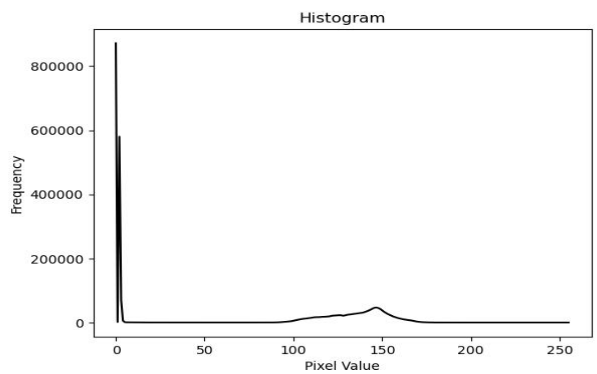
Sample 1



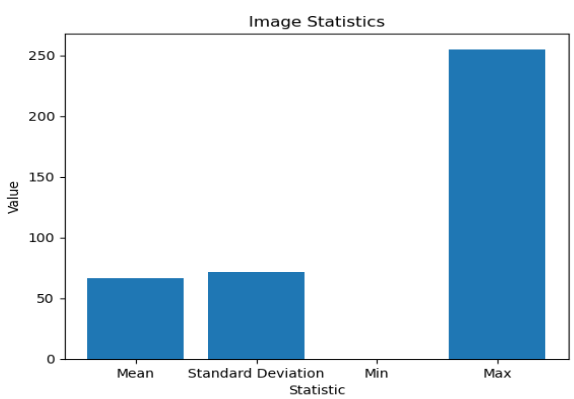


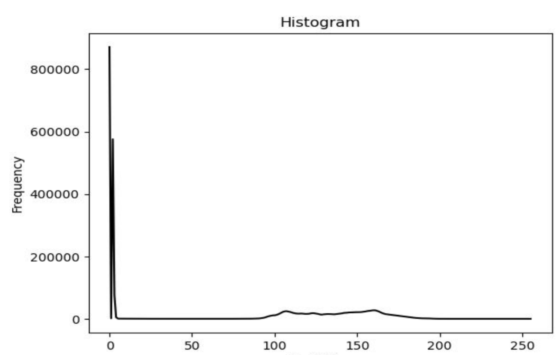
Sample 2



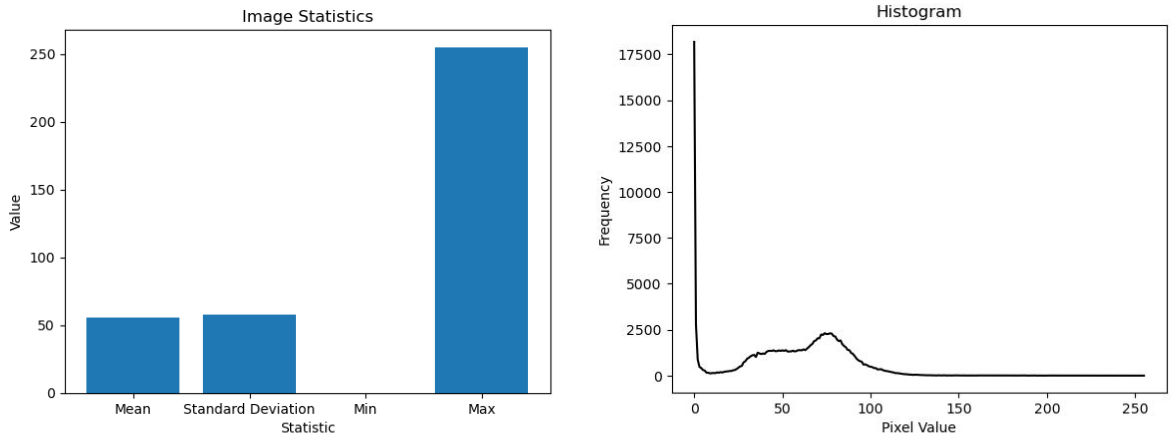


Sample 3

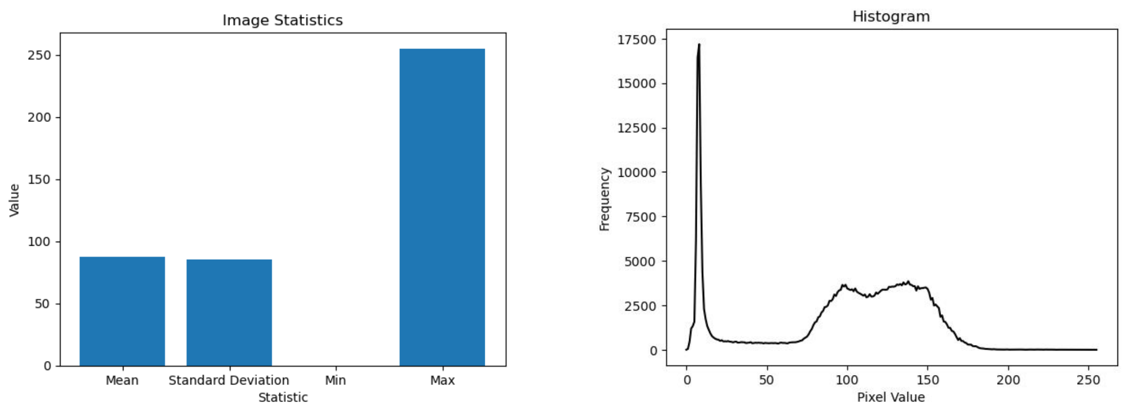




Sample 4



Sample 5



Conclusion

The applied techniques and methodologies extract a sufficiently good amount of data from the medical images to analyze the data qualitatively and quantitatively, required for better diagnosis of medical images even with a bulk data.

References

1. *A. Mittal, A. K. Moorthy and A. C. Bovik, "No-reference image quality assessment in the spatial domain", IEEE Trans. Image Process., vol. 21, no. 12, pp. 4695-4708, Dec. 2012.*
2. *Q. Li, W. Lin and Y. Fang, "No-reference quality assessment for multiply-distorted images in gradient domain", IEEE Signal Proc. Lett., vol. 23, no. 4, pp. 541-545, Apr. 2016.*
3. *W. Xue, X. Mou, L. Zhang, A. C. Bovik and X. Feng, "Blind image quality assessment using joint statistics of gradient magnitude and Laplacian features", IEEE Trans. Image Process., vol. 23, no. 11, pp. 4850-4862, Nov. 2014.*
4. *Routhu Shanmukh, CH Nooka Raju, Syed Raashid Andrabi, "Analysis of intensity variations on applications of edge detection techniques to fundus images", GRADIVA REVIEW JOURNAL, VOLUME 9 ISSUE 1 Jan-2023.*
5. *H. Sheikh, A. Bovik and G. de Veciana, "An information fidelity criterion for image quality assessment using natural scene statistics", IEEE Trans. Image Process., vol. 14, no. 12, pp. 2117-2128, Dec. 2005.*
6. *Tolhurst, D. J., Movshon, J. A. & Dean, A. F. The statistical reliability of signals in single neurons in cat and monkey visual cortex. Vis. Res. 23, 775–785 (1983). 8.*
7. *Abadpour A., Kasaei S.: A fast and efficient fuzzy color transfer method. In Proceedings of the 4th IEEE International Symposium on Signal Processing and Information Technology (2004), pp. 491– 494.*
8. *Billock V. A., Cunningham D. W., Havig P. R., Tsou B. H.: Perception of spatiotemporal random fractals: an extension of colorimetric methods to the study of dynamic texture. Journal of the Optical Society of America A, 18, 10 (2001), 2404– 2413.*
9. *Billock V. A., Cunningham D. W., Tsou B. H.: What visual discrimination of fractal textures can tell us about discrimination of camouflaged targets. In Human Factors Issues in Combat Identification, D. H. Andrews, R. P. Herz, M. B. Wolf (Eds.), Ashgate, Surrey, England (2009), pp. 99– 112.*
10. *Bach F. R., Jordan M. I.: Kernel independent component analysis. Journal of Machine Learning Research, 3 (2002), 1– 48.*
11. *Campbell F. W., Howell E. R., Johnson J. R.: A comparison of threshold and suprathreshold appearance of gratings with components in the low and high spatial frequency range. Journal of Physiology, 284 (1978), 193– 201.*
12. *Deussen O., Colditz C., Coconu L., Hege H.: Efficient Modeling and Rendering of Landscapes Visualization in Landscape and Environmental Planning. Taylor & Francis, Oxon , England , 2005.*
13. *Deussen O., Colditz C., Coconu L., Hege H.: Efficient Modeling and Rendering of Landscapes Visualization in Landscape and Environmental Planning. Taylor & Francis, Oxon , England , 2005.*
14. *Field D. J.: Scale-invariance and self-similar 'wavelet' transforms: an analysis of natural scenes and mammalian visual systems. In Wavelets, fractals and Fourier transforms, M. Farge, J. C. R. Hunt, J. C. Vassilicos (Eds.). Clarendon Press, Oxford (1993), pp. 151– 193.*
15. *Fergus R., Singh B., Hertzmann A., Roweis S., Freeman W.: Removing camera shake from a single photograph. ACM Transactions on Graphics, 25 (2006), 787– 794.*
16. *Finlayson G., Trezzi E.: Shades of gray and colour constancy. In Proceedings of the Twelfth Color Imaging Conference (Scottsdale , AZ , 2004), pp. 37– 41.*
17. *Gijsenij A., Gevers T.: Color constancy using natural image statistics. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (Minneapolis , MN , 2007), pp. 1– 8.*
18. *Graham D. J., Redies C.: Statistical regularities in art: relations with visual coding and perception. Vision Research, 50, 16 (2010), 1503– 1509.*

19. *Huang J., Mumford D.: Statistics of natural images and models. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (Fort Collins , CO , 1999), vol. 1, pp. 541– 547.*
20. *Zhu, S.-C. (2003). Statistical modeling and conceptualization of visual patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence 25, 691–712.*
21. *Simoncelli, E.P. & Olshausen, B.A. (2001). Natural image statistics and neural representation. Annual Review of Neuroscience 24, 1193–1216.*
22. *O'Regan, J.K. & Noe, A. (2001). A sensorimotor approach to vision and visual consciousness. Behavioral and Brain Sciences 24, 939–973.*
23. *Parkhurst, D.J. & Niebur, E. (2003). Scene content selected by active vision. Spatial Vision 16, 125–154.*
24. *Rao, R. & Ballard, D.H. (1999). Predictive coding in the visual cortex: A functional interpretation of some extra-classical receptive-field effects. Nature Neuroscience 2, 79–87.*
25. *Reinagel, P. & Zador, A.M. (1999). Natural scene statistics at the center of gaze. Network: Computations in Neural Systems 10, 341–350.*
26. *Ringach, D.L. (2002). Spatial structure and symmetry of simple-cell receptive fields in macaque primary visual cortex. Journal of Neurophysiology 88, 455–463.*
27. *T. Brandão et al. No-reference image quality assessment based on DCT domain statistics, Signal Process, (2008)*
28. *X. Gao et al. Wavelet-based contourlet in quality evaluation of digital images, Neurocomputing, (2008)*
29. *H.R. Sheikh et al.A statistical evaluation of recent full reference image quality assessment algorithms, IEEE Trans Image Process, (2006)*
30. *Routhu Shanmukh, CH Nooka Raju, Lakshmana Rao Rowthu, "Analysis of fundus images using conventional edge detection techniques" , Journal of Information and Computational Science, pp. 206-217, Dec-2022.*
31. *C. Huang, L. Zhang, J. Fang and Q. Tong, "A radiometric calibration model for the field imaging spectrometer system", IEEE Trans. Geosci. Remote Sens., vol. 51, no. 4, pp. 2465-2475, Apr. 2013.*
32. *M. Wegener, "Destriping multiple sensor imagery by improved histogram matching", Int. J. Remote Sens., vol. 11, no. 5, pp. 859-875, May 1990.*
33. *R. E. Crippen, "A simple spatial filtering routine for the cosmetic removal of scan-line noise from Landsat TM P-tap imagery", Photogramm. Eng. Remote Sens., vol. 55, no. 3, pp. 327-331, Mar. 1989.*
34. *Levin A., Zomet A., Weiss Y.: Learning how to inpaint from global image statistics. In Proceedings of the Ninth IEEE International Conference on Computer Vision (Nice , France , 2003), pp. 305– 312.*
35. *A. Criminisi, P. Perez and K. Toyama, "Region filling and object removal by exemplar-based image inpainting", IEEE Trans. Image Process., vol. 13, no. 9, pp. 1200-1212, Sep. 2004.*