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Texture Identification of Cancer Cell Using Tamura's Feature for Precise Treatment to Avoid Metastasis: A New Era of Artificial Intelligence in Healthcare Industry 5.0

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Abstract

Texture plays a significant role in image processing where the images are computed to detect mortal diseases like cancer. Artificial Intelligence (AI) finds various approaches in the level of industry expert 5.0 for the precise treatment of this disease which helps to motivate and inculcate patient's mind from the darkness of it. Cancer changes the structure of the affected area (cell and/or tissue and/or organ) in an irregular manner so the texture or coarseness of ROI (Region of Interest) changes rapidly in the patient's body. Tamura's feature is playing to detect different assessment parameters like linelikeness, coarseness, direction of texture, body roughness, smoothness, irregularity, contrast by which the model can assess whether a ROI of input dataset carcinogenic or not. This communication has detected the precise condition of the image of the affected area which helps medical practioner for proper diagnose and treatment to avoid metastasis. Here we use python 3.7 in Google Colab platform to execute the model. As the model is based on deep learning methodologies so this cloud platform helps us to reduce the computation time for big dataset.

Keywords

Machine Learning, Image Processing, Software as a Service, Carcinoma, Breast Cancer

1. Introduction

Cancer is one of the most unpredictable diseases where the percentage of fault diagnosis possibility is very low. The propagation rate of this disease is very high cumulative rate where the cancer granules spread from source organ to other unaffected organ or tissue. In the field of medical diagnosis, it is very difficult for medical practitioner to understand the pattern of the disease and its status which is varies from patient to patient as because this disease is mostly depends upon the immunity power of human body. The medical practitioner gives their idea and suggestions to the patient based on their reports. These reports are represented in the form of X-ray or CT (Computed Tomography) or PET-CT (Positron emission tomography/Computed Tomography) or MRI (Magnetic Resonance Imaging). Mostly these technologies are adapting the essence of artificial intelligence (AI), or augmented reality (AR), virtual reality (VR), 3-D printing or digital twins. Mostly these applications are based on invariant shape descriptor tool based. Shape descriptor is a tool which finds out the shape and size of the target object. If the object moves or distorted from its origin, then also the basic shapes of the object can be identified through this tool. So, the actual shape or size of the source and its orientation or distortedness can be possible to be diagnosed by the medical practitioner. The molecular weight of tissue is related to that of bone like calcium which is 40.

But the status or desiredness of dynamic cell-oriented disease is very difficult for medical practitioners to predict by seeing the report or scanned or transformed images only. Texture of the cell plays an important role here for the better understanding of the disease. It is inherited inherited from the term texture where it explained the internal architecture of the different protein-protein (P-P) and non-protein-protein (NP-P) and non-protein-non-protein (NP-NP) fiber structure. The cancer cell microenvironments relate to different types of cells due to their dynamic nature which accelerates the disease progress. The texture of the affected cell or tissue tells a brief idea about the internal architecture of the region of interest (ROI). It contains cell contrast, cell-pattern linelikeness, cell-structure directionality, cell-surface roughness, cell-pattern regularity, cell-internal or external coarseness etc. All these assessment parameters are combining and forming a human cognitive based perception pattern features which is known as Tamura’s representation. It is one kind of shape descriptor oriented which gives shape ideas or texture pattern whereas the target source is translated or rotated or sheared. Normally this feature does not work properly for derived images due to their complexity and heterogeneity surface or structures. To detect the heterogeneous structure of the pattern Tamura’s feature can import various kernel convolution structure. Using heterogeneous kernel structure it can improve signal-to-noise rate, detect image after long treatment, detect depth of texture pattern of image, reduce phototoxicity etc.

In industry 5.0 as per Figure 1 with the help of cognitive human robots which are termed Cobots, we can optimize the treatment duration and procedures. In industry 3.0 we have introduced automation in various sectors and mostly in healthcare platforms.

In industry 4.0 we have seen the advantages of internet of things (IoT) in healthcare sector. But 5.0 is mostly an introduction to human feelings. It should be much technology based but it also human blended. The introduction of human robots using cognitive system approaches tries to optimize the medical methodologies which are human oriented and reduce their anxiety.

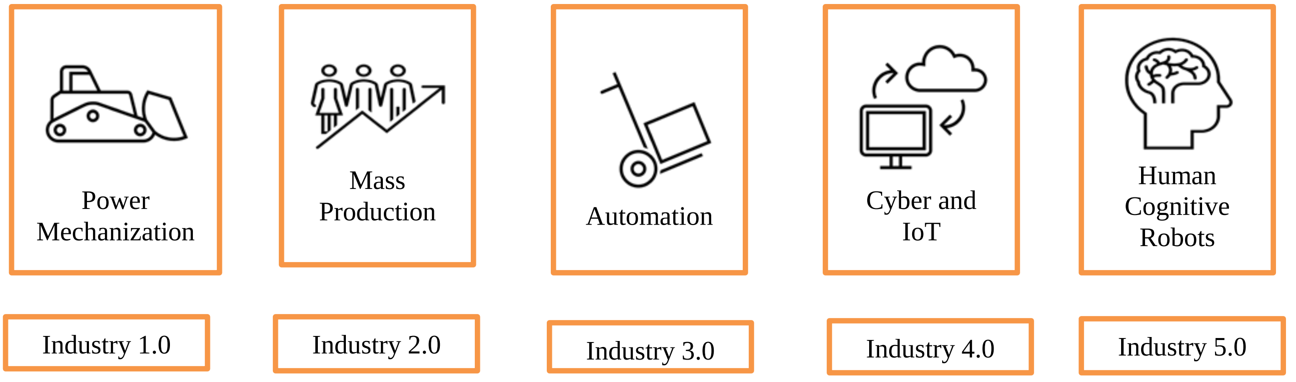


Figure 1. Taxonomy of Industry Experts levels

2. Literature Study

Karmakar et al [1] has introduced an improved version of Tamura's feature based on kernel descriptor tool. Here in this communication, it has shown similarity between patches of two images. It has proposed a set of kernel descriptor tools for the new features of it. Martino et al [2] has worked on components of tumour microenvironment which has indicated the texture features of fibrinogen granules within it. Reis et al [3] has shown that the presence of biomarkers and their varieties in the cancer cell. Fontana et al [4] has produced a model based on lung cancer dataset which was in the initial state. Bhatia et al has [5] shown that texture pattern model approach has worked on deep learning approach. It has shown various comparison strategies which are based on machine learning and deep learning neural network algorithms using CT images of lung cancer. Vendrell et al [6] has explained a new methodology based on Raman scattering to show the texture pattern of the surface of the cell or tissue. It has worked on image datasets of histopathological biopsy datasets. Navid et al [7] has given a review communication on cancer diagnosis based on skin melanoma to import a model for automatic identification of metastasis stage. In Ahuja et al [8] we have learnt a Convolution neural network based (CNN) based model for the detection of Lung CT slices datasets for the detection of covid. Here this model also has detected the texture pattern of the stated image dataset.

3. Texture of Cancer Cell

The texture of a cancer cell refers to its physical and structural characteristics, which can be observed under a microscope or analyzed through various imaging techniques. Cancer cells typically exhibit distinct features that differentiate them from normal cells [9-12].

3.1. Abnormal Shape and Size

Cancer cells often have irregular shapes and sizes compared to normal cells. They may be larger or smaller than surrounding healthy cells and may display an asymmetrical or distorted morphology [13-14].

3.2. Increased Nucleus-to-Cytoplasm Ratio

Cancer cells tend to have a higher ratio of nucleus to cytoplasm compared to normal cells. This increased ratio is a result of the rapid and uncontrolled cell division characteristic of cancer [13-14].

3.3. Nuclear Abnormalities

The nucleus of a cancer cell may show abnormalities such as enlarged size, irregular shape, and uneven distribution of chromatin. These changes are indicative of genetic alterations within the cell [15-16].

3.4. Disorganized Tissue Structure

In solid tumors, the tissue structure is often disorganized, with cancer cells forming chaotic arrangements rather than the organized patterns seen in normal tissues.

It's important to note that the texture of cancer cells can vary depending on the type of cancer, its stage, and other individual factors. Histopathologists and medical professionals often rely on detailed microscopic examinations and various imaging modalities to assess these characteristics and make accurate diagnoses.

4. Methodology and Result Discussion

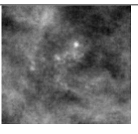
Tamura's feature is based on various assessment parameters of the image like shape of the image, contrast of the image, directionality of the texture, roughness of the surface or smoothness of it, coarseness of the texture pattern etc. Contrast of the texture pattern means the brightness of the surface of the cell. It has indicated the number of the presence of the pixel within it. Directionality of the pattern means that determined by plotting the frequency distribution of oriented local edges against their directional angles. If any discreteness is found within the cell surface or internal structure, then the directionality value has shown an abstract nature which is mentioned in the output table no 1. Coarseness of the surface has a direct connection with the scale and repetition of the texture within the surface. Multiple presence of cancer biomarker has been detected by this feature. Roughness of the texture means that the summation value of the coarseness and contrast of the it.

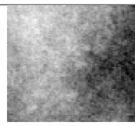
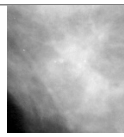
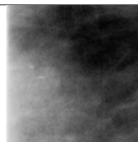
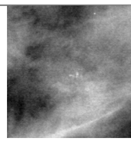
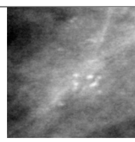
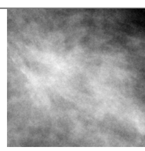
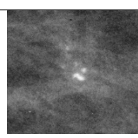
Here in this communication CBIS-DDSM [17] has been used as the input dataset. The model was developed in python 3.7 version in Google Colab cloud platform which is known as Software as a Service (SaaS). In table 1 the output data is shown below where we represent the type of the dataset, its representation, shape, contrast, directionality, roughness, and coarseness. There are more three attributes present as Tamura's features such as Linelikeness, regularity and co-occurrence which can be easily derived from those values.

CBIS-DDSM [17] is one of the most authentic datasets of breast cancer from where we have chosen only fused sample. In earlier in our research, we have failed to apply our model upon few datasets where the disease may propagate as metastases stage [18-20]. Here in this approach, we have used only those samples to reduce our previous drawback. So, the input dataset has been taken in a random manner from the data repository.

As per table 1 we have seen the types of images (fused state) and their corresponding Tamura's value. The discreteness of the values indicated that all the sample input dataset has been affected by metastasis stage. The values of the assessment parameters are not in synchronous manner. Using this kind of asynchronous value, the precise identification of metastasis stage through the cell texture may be possible to determined.

Table 1 Output dataset for the used sample image

SL No.	Image Type	Image Dataset	Image Shape	Contrast	Directionality	Roughness	Coarseness
1	263		(211, 226)	24.823483	752.301040	33.965349	9.141866

2	031		(81, 89)	40.405530	942.179338	47.2713922505942	6.865862
3	047		(537, 497)	31.108063	851.475560	40.73882334751771	9.630760
4	037		(401, 305)	44.116724	555.653696	52.89691272461452	8.780189
5	118		(365, 341)	33.684926	1060.003989	43.697507695797356	10.012582
6	064		(364, 334)	41.205996	521.353979	51.523879510117176	10.317883
7	199		(266, 191)	32.062421	508.238490	41.2115176545392	9.149097
8	162		(386, 436)	32.901419	842.428565	43.36697340114224	10.465555
9	281		(233, 249)	12.549912	937.398233	21.22137049257693	8.671458
10	033		(327, 370)	49.721121	548.533309	59.99689586058645	10.275775

5. Conclusion

Tamura's feature has been playing a significant role in the search of texture or pattern of the surface of cell or tissue. It has introduced many image assessment parameters for the identification of status of the internal structure of the cell. Cancer propagates through cells in an imprecise way so preciseness of diagnose process of this disease is very important. In this communication we have shown the approach of Tamura's feature for the detection of metastases phase of this disease. Here the model has been developed in Cloud platform (Colab) using python where the computation speed and size are very optimum in nature. The model can identify the various attributes of that feature irrespective nature and shape of image dataset. As per industry expert 5.0 the model has derived as human blended healthcare tool where the output of cancer disease has solved in an optimized way.

Conflicts of Interest

We hereby certify that, to the best of our knowledge, the work which is reported on in said manuscript has not the submitted work was carried out in the presence of any personal, professional, or financial relationships that could potentially be construed as a conflict of interest.

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