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Enhanced Tissue Classification Based on Multi Attribute Sectional Light Absorption Estimation Using Fuzzy Rule Sets

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Abstract: Tissue classification has become more sophisticated in medical domain where the classification of tissues are performed with the spectra meter. There are many approaches has been discussed for the development of tissue classification, but struggles with the problem of less accuracy and false classification ratio. We propose a multi attribute light absorption estimation technique using fuzzy rule set. The method passes the light from the spectra meter over the tissue and the skin reflects certain amount of light reflected is identified. Also the method computes the area of the tissue and the area of light deployment, the strength of light rays being received. With these features the method computes the region based light absorption by computing the light being received or reflected at each section or region of the tissue image. Using the computed multi attribute sectional light absorption values, the method generates number of rules to perform image classification. At the training phase, the method segments the input set image and for each class of image the method extracts the area of diseased skin, the amount of light being applied and the strength of light being received and so on. The rule set is generated from these data and matched with the input feature vector to compute the similarity which the tissue classification is performed.

Index terms: Tissue Classification・Fuzzy Rule Sets・Multi Attribute Light Absorption・Image Segmentation

INTRODUCTION

The medical industries has adapted various solutions to diagnose different diseases affected by human being and in many cases they use the medical image captured by X-Ray, CT-Scan, Multi Resolution Images which represent the human anatomy component in gray scale image. By simply viewing these images the medical practitioner could not decide anything about the disease affected. So they need some support from the automated solutions which performs such identification process using medical image processing techniques.

Image processing techniques has various stages like preprocessing, feature extraction and segmentation and classification. The preprocessing stage is the generic one which removes the noise from input image and enhance the image quality. Feature extraction is the important stage of processing and the result of the method is hugely depend on the kind of feature being considered. Some methods uses, shape, color, gray values, object as the feature to perform the image classification. By using or identifying the feature the segmentation process, groups the pixels belongs to such features and produces an segmented image. From the segmented image the medical practitioner could identify what is what.

The medical image classification can be applied to the problem of tissue classification, where the light source from the spectra meter is passed over the human anatomy. The human parts is composed of blood, melanin, water which are visible when its gets damaged due to accident of by affected by any disease. From the human skin itself, we can classify them as wounded, diseased and normal and so on. The human skin reflects some amount of light, if it is not damaged and the melanin also reflect little bit of light energy by the water source absorbs light and does not reflect. Using the property of human anatomy the problem of tissue classification can be solved, using the light based techniques.

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For the problem of tissue classification, it requires more samples to be trained because, in case of wound, the skin color may be changed and the part of skin would reflect only little amount of light. Also the amount of reflection and the strength of light source is depend on the area of the skin being wounded or diseased. So in order to classify the tissue image efficiently, the method has to train more samples in each class and can convert the trained feature into rule sets. The fuzzy rule sets can be adapted to the technique of tissue classification, by training more samples and based on the features of the tissue and the light being absorbed, reflected.

The fuzzy rule can be generated by including multiple attributes of the tissue like, area of overall skin, area of skin, area of melanin, area of water, color values of skin region, amount of light passed, amount of light being reflected, strength of light passed and reflected. By generating rule based on the mentioned features or values, the classification of image can be performed in efficient manner.

Related Works: There are many approaches has been discussed earlier for the classification of tissue and we discuss few of them here in this section.

Intraoperative Tissue Identification Using Rapid Evaporative Ionization Mass Spectrometry [1], is an emerging technique that allows near–real-time characterization of human tissue in vivo by analysis of the aerosol ("smoke") released during electrosurgical dissection. The coupling of REIMS technology with electrosurgery for tissue diagnostics is known as the intelligent knife (iKnife). This study aimed to validate the technique by applying it to the analysis of fresh human tissue samples ex vivo and to demonstrate the translation to real-time use in vivo in a surgical environment. A variety of tissue samples from 302 patients were analyzed in the laboratory, resulting in 1624 cancerous and 1309 noncancerous database entries. The technology was then transferred to the operating theater, where the device was coupled to existing electrosurgical equipment to collect data during a total of 81 resections. Mass spectrometric data were analyzed using multivariate statistical methods, including principal components analysis (PCA) and linear discriminant analysis (LDA) and a spectral identification algorithm using a similar approach was implemented. The REIMS approach differentiated accurately between distinct histological and histopathological tissue types, with malignant tissues yielding chemical characteristics specific to their histopathological subtypes.

Human skin wounds: a major and snowballing threat to public health and the economy [2], In the United States, chronic wounds affect 6.5 million patients. An estimated excess of US$25 billion is spent annually on treatment of chronic wounds and the burden is rapidly growing due to increasing health care costs, an aging population and a sharp rise in the incidence of diabetes and obesity worldwide. In fact, chronic wound patients frequently suffer from "highly branded" diseases such as diabetes and obesity. This seems to have overshadowed the significance of wounds per se as a major health problem. The need for post-surgical wound care is sharply on the rise. Emergency wound care in an acute setting has major significance not only in a war setting but also in homeland preparedness against natural disasters as well as against terrorism attacks.

Segmentation and analysis of the tissue composition of dermatological ulcers [3], propose color imaging and image processing methods. Methods considering the bottom tissues are proposed for the segmentation of a given image into regions corresponding to red granulation, yellow fibrin, black scar and white hyperkeratotic tissue (callous). Tests with 172 images and comparison with visual analysis by a dermatologist indicated an average root-mean-squared error of 22.7% in tissue composition. In retrospective analysis, the dermatologist indicated that the results were accurate for 31.4% and acceptable for 14% of the images. Comparison between the lesion area obtained automatically and the same lesion region manually drawn by a dermatologist indicated an average superposition of 0.61.

Towards a comprehensive assessment of wound-composition using color-image processing [4], reports the results of our work on assessing wound-composition based on color-image processing. A knowledge-base (reference-clusters in the 3D color space) of different categories of wound-tissue and pigmentation was built, using about 9000 pixels from 48 images of various wounds. The HSI model was used for the purpose. We address 8 categories of wound-tissue and pigmentation, many more than those reported so far in the literature. The knowledge base was used subsequently for assessing wound-composition, through classification based on Mahalanobis distance. The results of experiments to test the efficacy of the algorithm are encouraging.

Automated leukocyte recognition using fuzzy divergence [5], introducing an automated approach to leukocyte recognition using fuzzy divergence and modified thresholding techniques. The recognition is done through the segmentation of nuclei where Gamma, Gaussian and Cauchy type of fuzzy membership functions are studied for the image pixels. It is in fact found that Cauchy leads better segmentation as compared to others. In addition, image thresholding is modified for better recognition. Results are studied and discussed.

Robust tissue classification for reproducible wound assessment in telemedicine environments [6], introduce the key steps including color correction, merging of expert labeling and segmentation-driven classification based on support vector machines. The tool thus developed ensures stability under lighting condition, viewpoint and camera changes, to achieve accurate and robust classification of skin tissues. Clinical tests demonstrate that such an advanced tool, which forms part of a complete 3-D and color wound assessment system, significantly improves the monitoring of the healing process. It achieves an overlap score of 79.3 against 69.1% for a single expert, after mapping on the medical reference developed from the image labeling by a college of experts.

Feature Based Classifiation of Lung Tissues for Lung Disease Diagnosis [7], propose a new method for Lung tissue Classification using Patch adaptive sparse approximation with two feature descriptors is proposed. Operator assisted classification methods are impractical for large amounts of data. High resolution Computed Tomography images contain a noise caused by operator performance which can lead to serious inaccuracies in classification. We design two new feature descriptors for higher feature descriptiveness, namely the rotation-invariant Gabor-local binary patterns (RGLBP) texture descriptor and multi-coordinate histogram of oriented gradients (MCHOG) gradient descriptor. Each image patch is then labeled based on its feature approximation from reference image patches. Decision making was performed in two steps i) Feature extraction using the two feature descriptors ii) classification using Patch adaptive sparse approximation.

In Automated Tissue Classification Framework for Reproducible Chronic Wound Assessment [8], the red-green-blue () wound images grabbed by normal digital camera were first transformed into (hue, saturation and intensity) color space and subsequently the “” component of color channels was selected as it provided higher contrast. Wound areas from 6 different types of CW were segmented from whole images using fuzzy divergence based thresholding by minimizing edge ambiguity. A set of color and textural features describing granulation, necrotic and slough tissues in the segmented wound area were extracted using various mathematical techniques. Finally, statistical learning algorithms, namely, Bayesian classification and support vector machine (SVM), were trained and tested for wound tissue classification in different CW images. The performance of the wound area segmentation protocol was further validated by ground truth images labeled by clinical experts.

Automated Classification of Glandular Tissue by Statistical Proximity Sampling [9], circumvent the problem by an implicit representation that is both robust and highly descriptive, especially when combined with a multiple instance learning approach to image classification. The new feature method is able to describe tissue architecture based on glandular structure. It is based on statistically representing the relative distribution of tissue components around lumen regions, while preserving spatial and quantitative information, as a basis for diagnosing and analyzing different areas within an image. We demonstrate the efficacy of the method in extracting discriminative features for obtaining high classification rates for tubular formation in both healthy and cancerous tissue, which is an important component in Gleason and tubule-based Elston grading. The proposed method may be used for glandular classification, also in other tissue types, in addition to general applicability as a region-based feature descriptor in image analysis where the image represents a bag with a certain label (or grade) and the region-based feature vectors represent instances.

All the above discussed approaches has the problem of poor classification accuracy and produces more false positive results and produces more false indexing.

Proposed Method: The proposed multi attribute sectional light absorption estimation based tissue classification has the following stages namely preprocessing, segmentation, rule generation, tissue classification. We discuss each of the functional modules in detail in this section.

Preprocessing: At the preprocessing stage the input image quality is improved by performing histogram equalization which enhances the contrast and quality of the image. The enhanced image is applied with segmentation process. The segmentation is performed using the color values of each pixel, the segmentation approach uses multiple threshold values. The input image pixels are identified and their red intensity value is used to perform segmentation. If the red intensity is higher than particular threshold then it is considered as a different class. Also the method used other two threshold values to group normal tissue pixels and diseased pixel. The segmented image is used to generate the fuzzy rule sets.

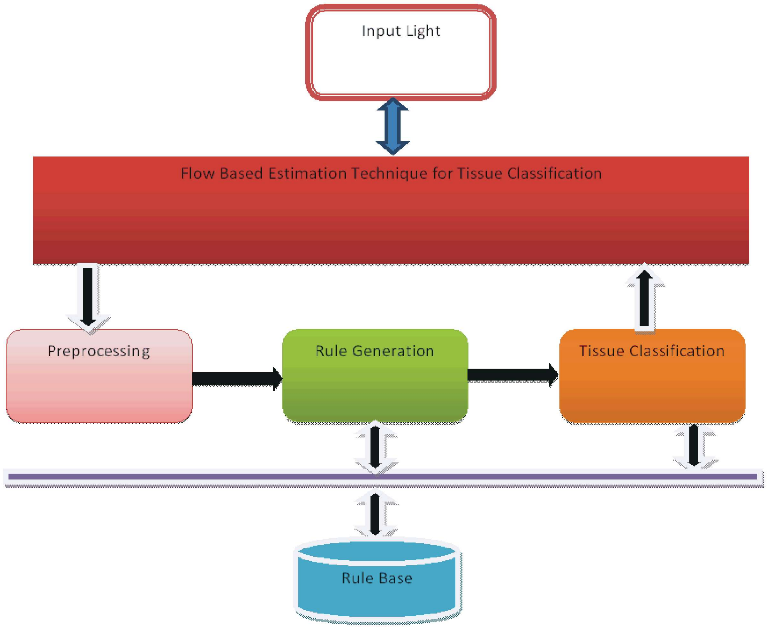


Fig. 1: Proposed System Architecture

Procedure:
Input: Tissue Image Timg
Output: Segmented image Timg.
Start
  Identify set of all unique intensity values of image Timg.
    Iv = Σ IntensityValues(Timg)□Iv
  For each intensity value Iv_i from Iv
    Compute probability distribution pdf = $\frac{\sum Pi(Timg)==Ivi}{Size(Iv)}$
    Restore the image pixel according to pdf.
  End.
  Extract the red layer from the image Timg.
    Rl = Timg(:,:,3).
  Find the unique intensity values from Rl.
    RIv = Σ IntensityValues(Rl) □ RIv
  Initialize segmentation thresholds NTh,DTh,WTh.
  For each pixel P_i from Timg
    If P_i(Timg).Intensity>(NTh+10)
      Assign to class A.
    If P_i(Timg).Intensity<(NTh+50)
      Assign Class B.
    If P_i(Timg).Intensity<(NTh+100)
      Assign Class C.
  End
Stop

The above discussed algorithm performs the segmentation of input tissue image and groups different pixels according to the red color intensity values.

The Figure 1, shows the architecture of the proposed approach and shows the functional components of the proposed system

Rule Generation: The method generates the rule according to the feature extracted from the image as well as the factor of light being reflected by the human tissue. The method generates infrared light from halogen lamp and applied through the human tissue. The light reflected from the tissues are collected using the spectrometer panel. The method generates number of small scale image and for each section the method computes the amount of light being reflected and the type of tissue identified in the section. The extracted feature is generated as a rule and added to the rule set.

Procedure:
Input : Segmented Image Simg.
Output: Rule Ri
Start
 Capture Image Img.
 Preprocess the image Img.
 Initialize box size X.
 Generate Integral Image IImg = Σ Images(Img)/X
 Initialize Spectrometer, Input Strength Ips, reflection strength rs.
 Pass halogen light
 Receive reflection light through spectrometer.
 Ips= $\int H(l) \times T$
 H- Strength of light from halogen
 T – Time duration.
 Compute reflection strength Rs.
 Rs = $\int H(l) - \emptyset(M + B + W) \times A(MBW)$
 M- Melenin B-Blood W-Water
 A – Area affected by MBW
 For each integral image I_i from IImg
 Compute light reflection rate Lrr = $\frac{A \times X}{Ips - Rs}$
 Generate Rule Ri = { A,Lrr, A.Type,…}.
 End
Stop

The above discussed algorithm uses the preprocessing stage and extract the features from the image and the light wave collected by the spectrometer.

Tissue Classification: The tissue classification is performed, using the rule set generated and the segmented image features. The method reads the rule set and the segmented image and performs the rule generation for the segmented image. Then with the rule set available, using all the rule available for each class of the tissue image, it computes the overall reflection factor. Then for the input image it computes the rule generation and then computes the overall reflection factor for the input image. By using both the measures, if the overall reflection factor of the input image falls within the range of the reflection factor of any class then it is assigned with the class.

Procedure:
Input: Rule Set Rs, Segmented Image Simg.
Output: Class C.
Start
 For each class of rule from rule set
  Collect the rules from the rule set.
  CRS = Σ Rules(Ci)_Rs
  For each Rule Ri from CRS
   For each section Si from Ri
    Compute Overall Reflection Factor ORF.

ORF = $\frac{\sum Ri(Si)}{size(Ri)}$

End

End

For each section Si from Ri

Compute average reflection factor Arf = $\frac{\sum ORF}{size(Ri)}$

End

End

Read Input Image Simg.

Generate Rule Rp.

For each class Ci

For each section Si

Compute cumulative reflection factor Crf.

Crf = Σarf(Ci(Si))-ReflectionFactor(si) $\frac{\sum Arf(Ci(Si))-ReflectionFactor(si)}{}$

End

End

Choose the Most close reflection class = Class(Min(Crf)).

Stop

The above discussed algorithm performs tissue classification using the fuzzy rule set and the intensity based segmentation algorithm.

RESULTS AND DISCUSSION

The proposed multi attribute sectional light absorption based tissue classification using fuzzy rule sets has been implemented and evaluated for its effectiveness in different ways. The proposed method has used light rays from halogen lamps and with various strength of wavelength from 600 nm to 1000 nm. The approach has been implemented in the scientific tool Matlab and for the evaluation the method has considered different skin types namely Normal skin, wounded skin, burned skin and diseased skin.

The Table:1, shows the test results of various properties of optical lights which is generated on a normal skin.

The transmittance value is computed by comparing the intensity values of incident light and transmitted light. It has been calculated according to Beer's law as follows:

$$\text{Transmittance } Tr = I / Io \tag{1}$$

where I- transmitted light and Io – incident light.

Similarly the absorption property represents the amount of light absorbed by the skin. It is calculated as follows:

Table1: Forearm Obtained by proposed method

	Proposed Method		
Wavelength nm	Transmittance	Absorption	Scatter
600	77	0.132	0.10
700	79	0.124	0.09
800	82	0.098	0.071
900	88	0.0621	0.061
1000	92	0.0513	0.051

Table2: Comparison of results with different skins

Types of skin	Absorbed Light nm	Reflected Light nm
Normal Skin	110	890
Burned Skin	720	280
Wounded Skin	670	330
Diseased Skin	590	410

$$\text{Absorption } Ab = 2\text{-}\log_{10}\times \left(\frac{I}{Io}\times 100\right) \tag{2}$$

The Table 2, shows the comparison of results produced on various skins by the proposed method, with the constant light with the wavelength 1000 nm.

The Figure 2, shows the result of burned skin image produced by the proposed method and it has been tagged as a diseased one. The depth of burn is computed as follows:

$$\text{Depth of burn } DB = \int \frac{I}{Io}\times (L\times W) \tag{3}$$

L – length of the image, W-width of the image.

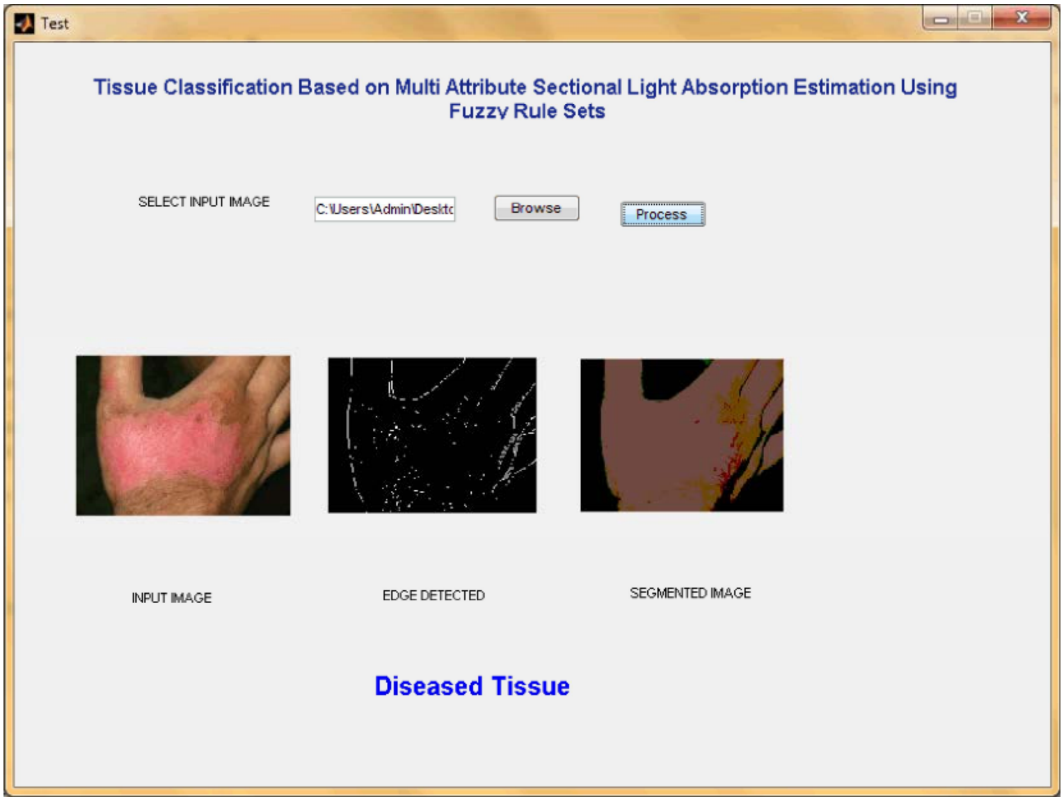
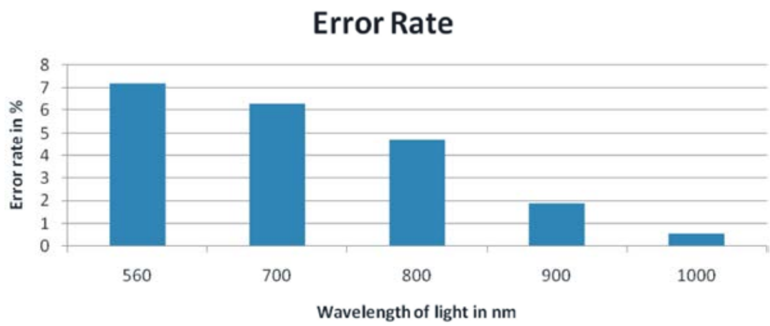
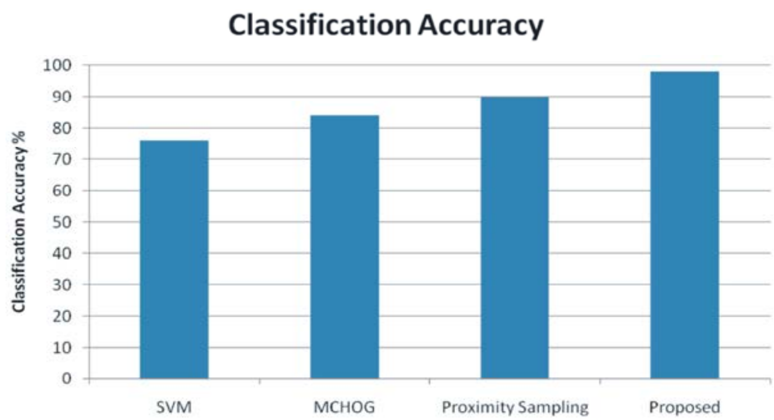


Fig. 2: snapshot of result produced on burned skin

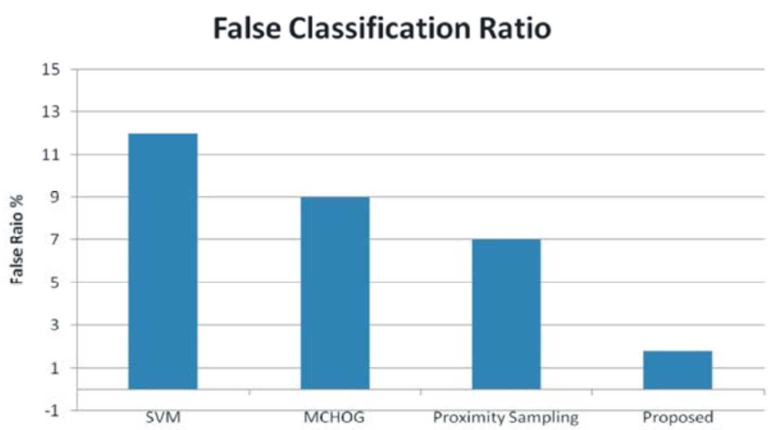
Fig. 3: Snapshot of result produced on wounded skin



Graph1: Comparison of error rate produced at different nm.



Graph 2: Comparison of classification accuracy



Graph 3: Comparison of false classification ratio

The Figure 3, shows the result produced by the proposed method on a given image with the optical light of wavelength 1000 nm. It shows that the method has classified the image as diseased one.

The wounded image is identified as a diseased image and the area of wound is calculated as follows:

$$\text{Area of wound Aw} = \int \frac{Absorption}{wavelength} \times (L \times W) \quad (4)$$

L – length of the image, W-width of the image.

The Graph 1, shows the error rate produced by the proposed method at different wavelength of light and it shows that the error rate is reduced when the wavelength is increased.

The Graph 2 shows the comparative result on classification accuracy produced by different methods and it shows clearly that the proposed method produces more efficiency than other methods.

The Graph 3, shows the comparative result on false classification ratio produced by different methods and it shows clearly that the proposed method has produced less false ratio than other method.

From the above analysis performed, the proposed method has been evaluated with various parameters and has produced efficient results with all factors of optical properties and classification.

CONCLUSION

We proposed multi attribute sectional light absorption technique using fuzzy rule sets for the classification of tissue images. The method removes noise from the input image and segments based on the intensity values. From the segmented image and the with the light absorption and reflection values the method generates sectional reflection rate at each section. The computed values are generated as a rule and added to the rule set. This will be performed at the training stage and the rule set is generated. At the testing set the same is performed for the input image and the rule generated for the input image will be compared with the other rules of each class and compute the overall cumulative reflection factor. Based on the reflection factor the image is classified into any one of the class. The Proposed method produces efficient results in accuracy of classification and reduces the error rate and time complexity also.

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