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SUPER RESOLUTION OF MRI BRAIN IMAGES USING MASKS AND FUZZY STRATEGIC RULES

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ABSTRACT
For the better medical diagnosis or treatment understanding and retrieval of information from the images, the process of image processing is having the very much importance. Because of simple process of modifying or interpreting the collected samples, it is becoming easier for the retrieval of information for the better treatment or diagnosis. Reconstruction of the high resolution image to gather complete information is necessary and it is dependent on the number of collected images which are at low resolution. But, it is expensive process to collect multiple numbers of sample images and it is difficult to obtain high resolution image from those low resolution images. Super Resolution image is the high resolution image obtained from a single or few low resolution images. In the proposal, obtaining super resolution image is implemented by using fuzzy strategic approach from single or few low resolution images that too on the most sensitive part of the human body i.e. Brain. In this paper masking process, fuzzy if-then rule and morphological operations are implemented to improve the resolution of the MR brain images to extract the complete details from the images. To assess the performance of the proposal different metrics are evaluated. And it is determined that the better results are obtained when compared with conventional methods.
Keywords: Low Resolution, Super Resolution, Mask, Fuzzy Strategy, Morphology

I. Introduction
In medical image processing, imaging with more quality will plays a vital role for the diagnosis or treatment in the critical instances [1]. Medical imaging is a powerful, structural sensory system which creates a visible representation of human body interior parts for medicinal analysis and due process. Magnetic resonance imaging (MRI) is a type of medical imaging [2], which is an incredible testing approach [3] gives proper anatomical images of the human body for brain, heart, liver, etc. But for medical images, enhancement is required as the visibility of important structures is scarce [4]. Especially, MR Brain images generally contain irregularity, uncertainty, inhomogeneity and divergence and therefore it is very challenging to extract the complete details of the image. Here for the human perception and intervention a method is proposed in this paper to increase the resolution, fuzzy strategy which handles uncertainty and vagueness [5].

Fuzzy logic is a higher cognitive process of artificial intelligence intended for the extension of multi-valued logic [6]. Fuzzy logic is flexible thought easy to understand and is liberal process to work on imprecise data. Fuzzy logic checks human reasoning which includes uncertainty data to generate decisions. The fundamental concept of Fuzzy Logic is the membership function, which defines the degree of membership of an input value to a certain set or category. Fuzzy Logic is implemented using Fuzzy Rules, which are if-then statements that express the relationship between input variables and output variables in a fuzzy way. The output of a Fuzzy Logic system is a fuzzy set, which is a set of membership degrees for each possible output value.

Histogram Equalization

Usually, the basic operation for the image enhancement is histogram equalization (HE). In basic HE process, the intensities are adjusted along the pixels which are taken at the quantified positions. Here, the pixels are equalized based on the cumulative distributive function (cdf) [7]. The significant spread of the intensity over the complete scale will increase the dynamic range of the intensity [8].

But this discriminative equalization process may improve the contrast of the background noise and over enhances [9] the brightness of image, so there may be the loss of information and in result error contour may appear in the image. And the problem in this equalization is that it is not applicable to small brighter and dark regions.

Adaptive Histogram Processing

So, in continuation to provide the remedy for HE an adaptive histogram process is implemented to reduce the information loss throughout the intensity scale even for smaller regions with their local cdf's [7, 8]. With this better histogram can be implemented over HE. But in this adaptive process the problem is its tendency to over amplify noise in comparatively homogeneous regions of an image. So, to take over all the artifacts of the HE and adaptive process in the proposal masking with fuzzy logic [9] is implemented to operate at each and every region.

II. METHODOLOGY

In order to increase the resolution of the MR brain image, in the proposal concepts of masking and fuzzy logic are applied. The process flow sequence of the proposal is shown in figure1.

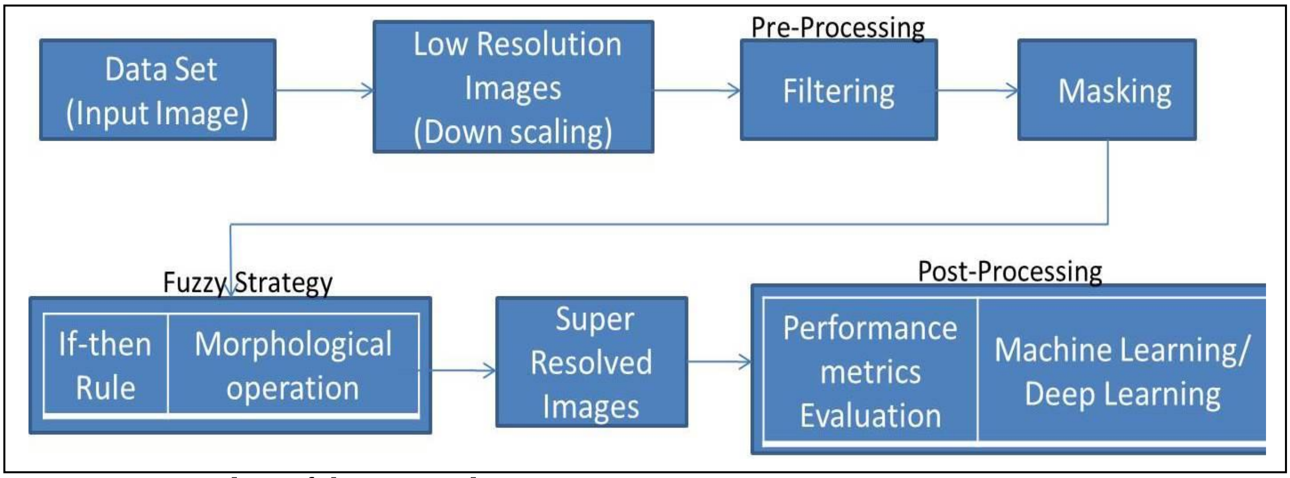

Figure 1: Process Flow of the proposal.

The input image on which the proposed method will be applied is taken as a reference data set. The images are scaled down to obtain the expected low resolution images. To remove any type of noise in the images during acquisition/scaling, a pre-processing operation filtering is implemented. Next on the image to increase the selected pixel intensities (region of interest), mask process is enforced. Masking is used to change the intensity value of any pixel position either to zero or non-zero value.

2.1 Mask Processing

In masking there is the chance of changing the intensity value of the uninterested part of the image to zero i.e. masks will remove the pixels which are inside or outside of the region of interest. In the proposal mask/area processing is used to change the pixel intensities to the maximum extent in the region of interest as shown in figure 2. A mask is a small matrix [10], in which the values can be treated as weights (Z1-Z9) as shown in figure 2 (a) with which the pixel values can be manipulated in an image [11].

With the weights, each pixel value can be changed by performing different operations like addition of all pixels, multiplication, convolution, etc. And also the pixel values can be changed to zero as shown in figure 2(b) or non-zero values in the region of interest as shown in figure 2 (c).

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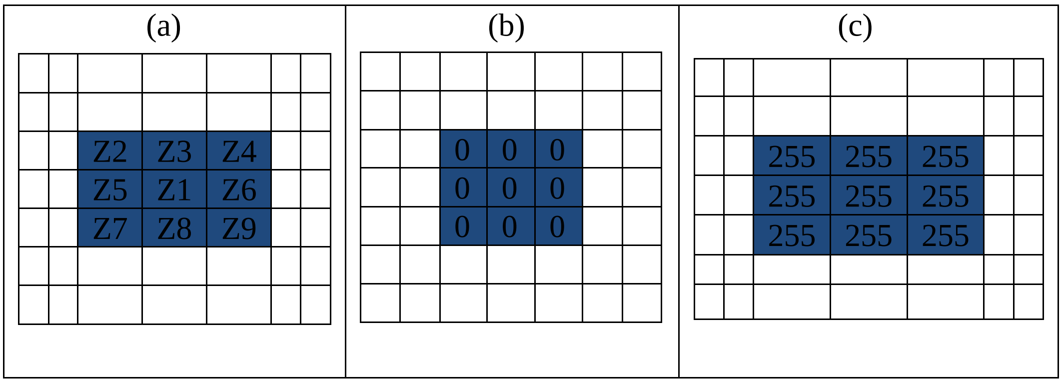

Figure 2: Mask/Area Process.

2.2 Fuzzy Strategy:

Along with mask/area processing, to improve the resolution of an image in the entire intensity scale fuzzy if-then [12, 13] logical rule is applied in addition to that morphological operation, dilation. Fuzzy rule consider a fuzzy set which represents the different levels of differentiation like low, medium and high values when compared with a classical rule which uses only two logical symbols 1 and 0. Usual form of the fuzzy logical rule is characterized with linguistic variables and linguistic values and it can be defined with antecedent and consequent operations as [14]

IF x is A then y is B, (1)

Where x and y are linguistic variables and A, B are linguistic values.

To categorize the image pixel intensity values based on the operation as in equation (1), a fuzzy set is formed with the intensity values as low, medium and high ranges. Now to improve the resolution of the entire image, lower and mid-range intensities are scaled up with a factor which forms a fuzzy subset and the complement of the image will be taken with a specified membership function as shown in the equations (2) & (3) respectively.

$\bar{A} = X - A$, (2)

Where *X* is the low resolution image, *A* is the fuzzy subset formed with scaling over *X* and $\bar{A}$ is the complement of *A*. And the membership function of the complement $\bar{A}$ is defined as [15]

$\mu_{\bar{A}}(x) = 1 - \mu_A(x)$, (3)

With the help of the formation of a specified fuzzy set, a morphological operation will be implemented to improve the resolution of the image. Here, dilation morphological operation [16] is applied to the fuzzy membership function so that the resolution increases with the full structuring element [17, 18]. And the proposed algorithm is summarized as follows:

2.3 Algorithm:

Step1: Input Image (a reference data set).
Step2: Scale down to obtain low resolution image and filtering.
Step3: Mask/area processing.
Step4: Fuzzy antecedent and consequent operations with if-then rule
Step5: Membership function generation
Step6: Morphological operation, dilation to obtain super resolved image.

The reference data set of six images (input image) and their low resolved images are shown in figure 3(a) & (b) respectively.

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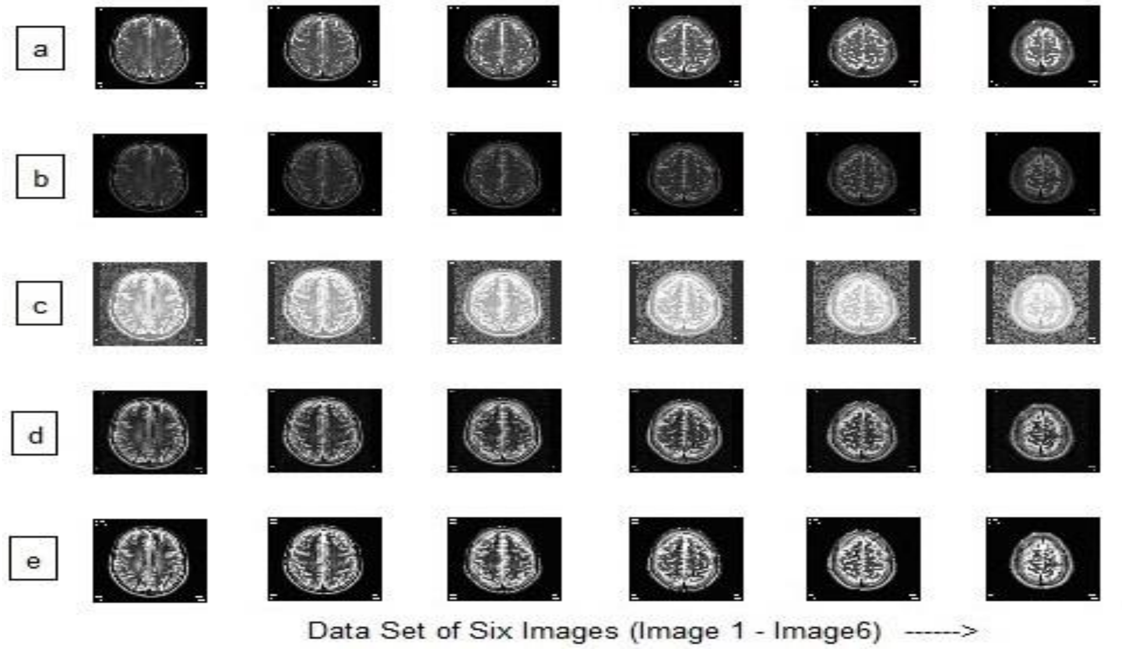

Figure 3. Enhancement of Images
(a) Reference Data Set; (b) Low Resolution image Set; (c) Histogramed Images; (d) Adaptive Histogramed images; (e) Fuzzy-Masking.

The enhancement of the images for the conventional approaches histogram and adaptive histogram process are shown in figure 3 (c) & (d) respectively. The enhancement for the proposed is shown in figure 3 (e) and it is observed that quite quality of the image is improved and is having quite better resolution when compared with the conventional methods.

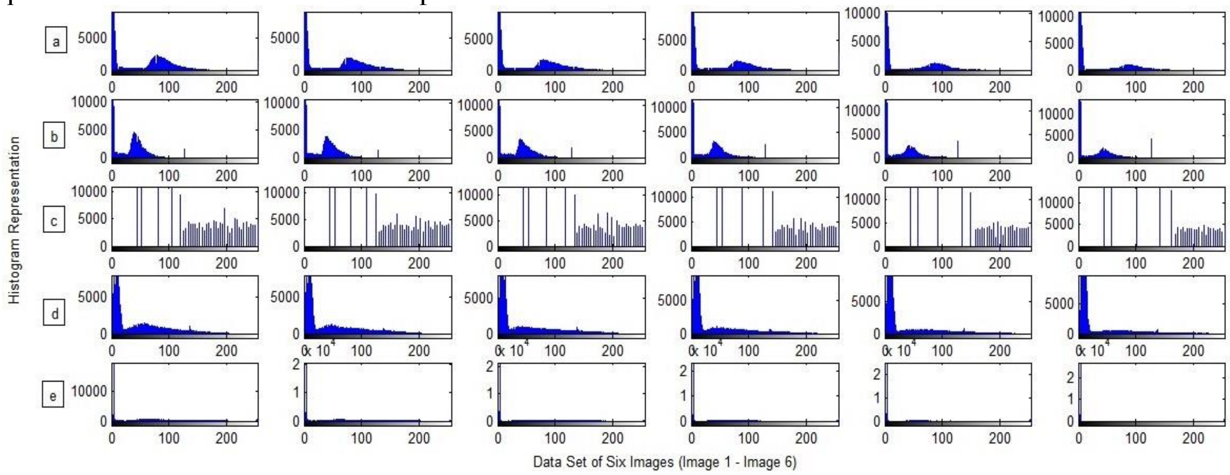

Figure 4. Histogram Equalization of the data set
(a) Reference data set; (b) Low Resolution Images; (c) Histogram Processing; (d) Adaptive Histogram; (e) Fuzzy-Masking.

To represent all the pixel intensities over the scale, histogram equalization [19] is very good graphical distribution of intensities for all pixels and is shown in the figure 4. Histogram equalization for the data set and low resolution images are shown in fig. 4 (a) & (b) respectively. And for the approaches histogram, adaptive and proposed the histogram equalization is represented in fig. 4 (c), (d) & (e) respectively.

III. **Evaluation of Image Metrics**:

The enhanced visual quality is not enough to justify the performance of the proposal. So, quantitatively to assess the proposal different image metrics are evaluated like peak signal to noise ratio (PSNR), absolute mean brightness error (AMBE) and entropy (E).

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PSNR:

It is the objective evaluation measure which represents the peak error measure between maximum power of original image and power of transformed image. This quality index quantifies the contentment of an individual human observer viewing the restored image compared to original image [20]. Higher the PSNR, high will be the image quality [21]. And numerically it is defined as

$$PSNR=20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right), \text{(In dB)} \quad (4)$$

Where MAXf is the maximum signal power in the original image and MSE is the accumulative squared error between the input and transformed images. The measured PSNR values for proposed and conventional approaches are graphically analyzed in fig. 5 and are tabulated in table 1.

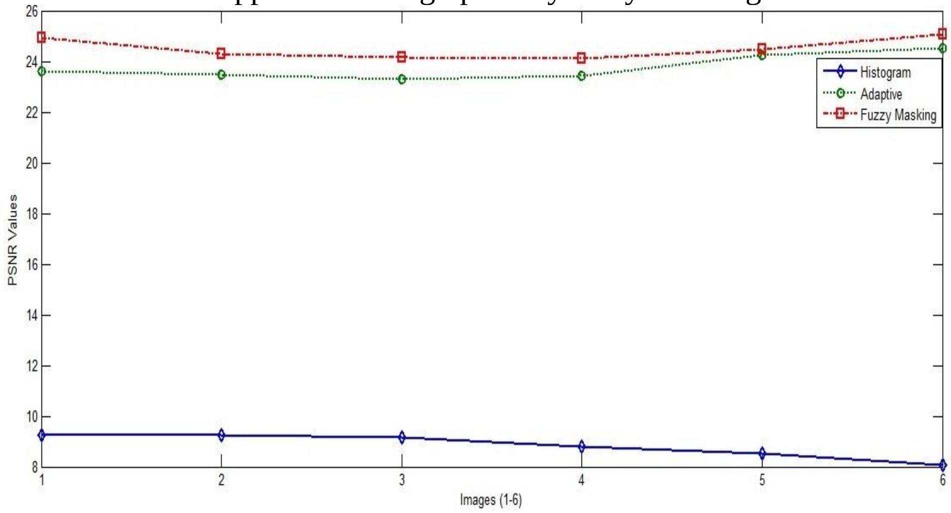

Figure 5: PSNR Analysis of the approaches

3.1 AMBE:

With the help of this quantitative metric, it is possible to estimate the amount of distortion with respect to the input image [22]. It can be defined as the mean brightness preservation error between the input and output (transformed) images [23] and is given by

$$AMBE=|m(x)-m(y)|, \quad (5)$$

Where m(x) and m(y) are the mean brightness of the input and output images respectively. Measured AMBE values for the taken data set are analyzed in the fig. 6 and the values are tabulated in table 2.

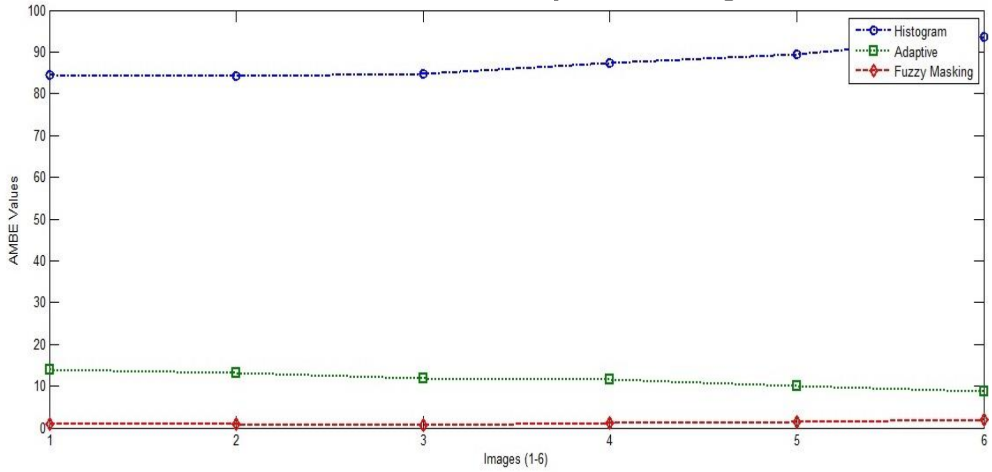

Figure 6: AMBE Analysis of the approaches

3.2 Entropy*:*

It is one of important parameter for the quantitative treatment to discern the details contained in an image. Entropy is a measure of choice and uncertainty [24], representing the corresponding state of the intensity level with reference to the pixel value [25]. Mathematically it is formulated as

$$E=-\sum_{i=1}^{L} m_i \log_2 m_i) , \quad (6)$$

Where *i* represent the greylevel, m is the probable existence of greylevel of *i* and L is the total number of greylevels. For the proposed and conventional methods, graphically the measured entropy values are analyzed in fig. 7.and the values are tabulated in table 3.

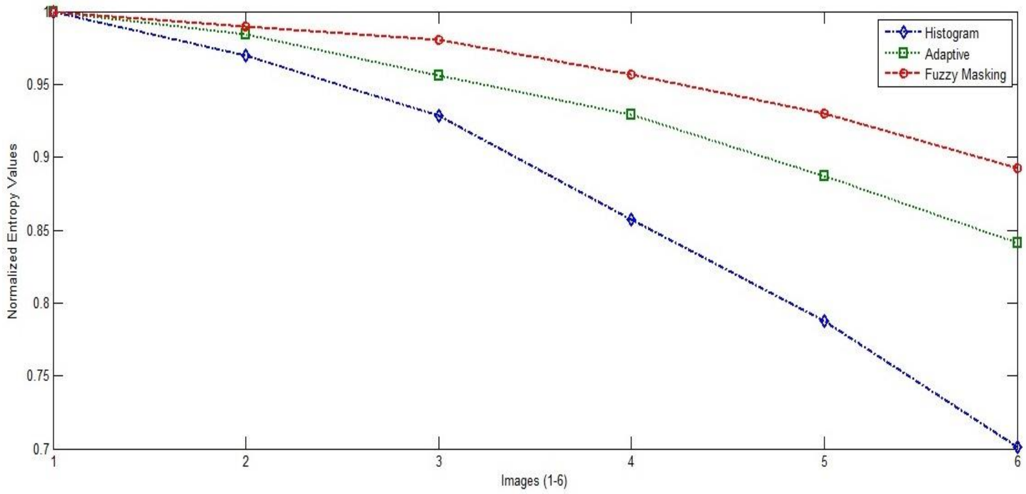

Figure 7: Entropy Analysis of the approaches

IV. RESULTS AND DISCUSSION:

As stated different performance image metrics are evaluated like PSNR, AMBE and entropy to analyze and compared the performance of the proposed method with the conventional methods. From the table 1 it is observed that high PSNR is achieved for the proposed method, so the higher quality of the image is obtained when compared with original image.

Table 1: PSNR Values for the approaches

Method / Images	Histogram	Adaptive	Fuzzy Masking
Image 1	9.23	23.62	24.92
Image 2	9.25	23.49	24.29
Image 3	9.15	23.29	24.16
Image 4	8.80	23.42	24.10
Image 5	8.51	24.26	24.50
Image 6	8.05	24.54	25.06

In table 2, AMBE values are indicated and approximately negligible error is achieved with the proposed method. As the error is reduced, it is easy to distinguish the constructed image with input image.

Table 2: AMBE Values for the approaches

Method / Images	Histogram	Adaptive	Fuzzy Masking
Image 1	84.41	13.85	0.94
Image 2	84.20	13.12	1.00
Image 3	84.70	11.97	0.65
Image 4	87.32	11.47	1.16
Image 5	89.58	10.07	1.55
Image 6	93.67	8.82	1.93

In table 3, measured normalized entropy values of the data set for the proposed method are displayed and are observed that better entropy is obtained when compared with the conventional methods. As entropy is better, it is easy to discern complete details of the image.

Table 3: Normalized Entropy Values for the approaches

Method Images	Histogram	Adaptive	Fuzzy Masking
Image 1	1.00	1.00	1.00
Image 2	0.97	0.98	0.99
Image 3	0.93	0.96	0.98
Image 4	0.86	0.93	0.96
Image 5	0.79	0.89	0.93
Image 6	0.70	0.84	0.89

V. Conclusion

Resolution enhancement of an image is most combat-ready research field in the image processing. For MR brain image resolution enhancement there exists variety of progressive methods, but the challenging is to reconstruct the high resolution image from the single or few number of low resolution images instead of multiple number of low resolution images as it is time consuming to take multiple samples and complex process. So, in the proposal it is achieved that the super resolution i.e. high resolution image which is constructed from single image sample and better results are obtained when compared with conventional methods in the means of performance metrics. Therefore fuzzy masking is a best approach to get the super resolved image in the less computation time with reduced error and improved PSNR, entropy. So, with the proposed it is easy to extract discern details of an image from MR brain images which can help to take the decision to give proper treatment/diagnosis. It is recommended that it can be very helpful for the better diagnosis in the critical time instances to save the mankind. In future there can be the potential to upload the data to cloud to implement in machine learning/deep learning for further processing.

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