# Plaque Lesion Classification Fuzzy Model Based on Various Color Models

Yuslinda Wati Mohamad Yusof, Hadzli Hashim, Khairul Anam Sulaiman,
Suhaila Subahir, Noor Ezan Abdullah and Fairul Nazmie Osman
Faculty of Electrical Engineering
Universiti Teknologi Mara (UiTM)
Shah Alam, Malaysia
yuslinda@salam.uitm.edu.my, hadzli66@gmail.com, s.khairul@ymail.com, suhailas@salam.uitm.edu.my,
ezan_nea7@yahoo.com , fnazmie81@yahoo.com

***Abstract* – This paper investigates discrimination of plaque lesion from other types of psoriasis lesions using fuzzy logic technology. The proposed intelligent model can aid dermatologist in doing pre-diagnosis of psoriasis lesion particularly in hospitals that are scarce of expert persons. Skin lesions can be represented in terms of enhanced image pixel indices from various color models such as *RGB, HSV* and *YCbCr*. These indices are used as inputs in designing an intelligent model based on fuzzy algorithm. However prior to that, numerical analysis is done statistically in order to select only significant color components that would infer plaque discrimination from the non-plaque group samples. The outcome of the designed fuzzy model has produced sensitivity and specificity of 72.72% and 90.09% respectively. Eventually, the overall accuracy of the fuzzy model is 81.82%, and is about 7% higher when compared to the optimized ANN model developed earlier from previous work.**

***Keyword*** *– **RGB; HSV; YCbCr; Fuzzy logic; MATLAB; SPSS.***

## I. INTRODUCTION

Psoriasis comes from the Greek word *psora*, meaning the state of being affected with itch. It is an immune mediated, genetic disease manifesting in the skin and/or the joints. This chronic scaling disease belongs to the papulosquamos diseases group of skin disorders [1]. In psoriasis, the epidermis layer beneath the outer skin surface thickens because of an abnormality growth of melanocyte cells causing dilation of blood vessels for nourishment. The immune system then sends faulty signals that speed up the movement rate of these cells to the surface within days instead of weeks where they will pile up with the dead cells, sometimes creating white, flaky layer over a patch of an inflamed skin. Psoriasis is prevalence worldwide effecting 1% to 2% of the population [2]. In Malaysia, the top five skin disorders seen by dermatologists each year are psoriasis, chronic eczema, allergies, occupational dermatitis and acne [3]. About 3% of the citizen population was reported to suffer from psoriasis alone, compared to only 0.756% that was having malignant skin problems [4]. Psoriasis has variety of clinical presentations. The major ones are the scaly plaques, noduled guttate, reddish erythroderma, and sometimes creating pus in pustular. It may range from just a few spots anywhere on the body to large areas of involvement. Nevertheless, it is not contagious or spreadable from one part of the body to another or from one person to another. However, individuals with severe psoriasis have a profound emotional and social as well as physical impact on their quality of life [5]. The exact cause of psoriasis is unknown, but it is common that psoriasis is heritable [6].

Dermatology is about medical study on skin diseases or lesions [2]. The fundamental concept of learning practiced by dermatologist is by looking at the skin lesion, applying morphological learning method and then follow-up by differential diagnosis steps in order to identify the types of diseases. These methods would include matching the skin lesion appearance to the closest appearance photo from a library text as guidance for the diagnosis. Basically, dermatologist needs to know the preliminary spatial and spectrum information when diagnosing a skin lesion. Since the human eye has limitation in performing such difficult tasks, dermatologists sometimes would rely on true color digital imaging to assist them in their work. Nowadays, with the rapid advances in computer and video technology, producing such a low-cost biomedical imaging based on analysis of color and texture of skin lesions has become very feasible. These support systems not only enhance the dermatologist ability to communicate with patients and colleagues but the quantified data images can be used more efficiently and perhaps diagnose the lesion with better accuracy and efficiency [7].

Many research works have applied available computer vision technology and other sophisticated image processing techniques on capturing and improving images of skin lesions. Characteristics such as **A**symmetry in the shape of lesion, irregular lesion **B**order, variegated **C**oloring in the lesion and **D**iameter of the lesion are useful and important features for dermatologist whenever skin diagnosis is concerned [1]. All of the lesion features based on the **ABCD** rule can be proposed as the front-end inputs in designing an artificial intelligence for automated dermatological diagnoses of a specific lesion. In fact, several work concerning realization of this idea have already been described and implemented where artificial neural network (ANN) were used as the lesion classifier [8-10]. These work focused on discriminating malignant melanoma from other types of skin tumor based on color features where several color models have been experimented to describe the colors characteristics of melanoma in terms of means and variances. Such models are the primary *RGB*, spherical color coordinates (*CIE-*$L\alpha\beta$ ), relative chromaticity (*rgb*), *CIE-LUV*, and the non-linear transformation model of *YCbCr* and *HSV*. Other artificial intelligence related work that used fuzzy algorithm for skin color image segmentation of lesions

 ISBN: 978-1-61208-169-4 

was described in these literatures [12-14]. However, these works mainly focused only on enhancement of selected lesion segmentation that utilized *RGB* and *HSV* color models. No discrimination between lesions was reported.

Application of neural network in automated diagnosis of psoriasis skin lesion has been initiated by Hashim *et. al.* His investigation was on discriminating plaque lesion from other psoriasis using ANN algorithm where several color models were used and reported in these literatures [14-16]. Most of the trained optimized ANN models were trained using Levenberg-Marquardt algorithm and later, validated based on the receiver operating characteristic (ROC) curve that conveniently displays diagnostic accuracy expressed in terms of *sensitivity* and *specificity* with respect to selected threshold values. When comparing between color models, the investigations have shown that *HSV* is the best color space for discriminating plaque with accuracy of 75.21% [15]. This result will be used for comparison later on with the investigation outcome of this paper.

As an additional study of the previous work, investigation on using fuzzy algorithm is proposed as the pattern classifier based on various color models. Therefore, this paper described the scope of work in Section I, followed by methodology in Section II. Section III is for the results and discussion. Finally, Section IV is the conclusion of the findings.

## II. SCOPE OF WORK

Scope of this study is on designing an intelligent fuzzy model that can discriminate plaque from non-plaque group of lesions based on three color models *i.e. RGB*, *YCbCr* and *HSV*. Digital image processing technique is applied to produce quantitative color measurements. Each lesion sample from the respective group is represented by its differential mean pixel index which will be elaborated in the following section. The group indices are tested statistically using Statistical Package for Social Sciences (SPSS) tool in order to observe any discrimination through independent *t*-test and eventually, computation of measurement range with respect to the group's mean, upper and lower confidence limit (*UCL* and *LCL*) [17]. The information is then used as inputs to design intelligent model using a fuzzy algorithm.

## III. METHODOLOGY

### A. Data Collection

Three sets of digital images of psoriasis lesions representing plaque, guttate, and erythroderma were captured from psoriasis patients under controlled environment at the Hospital Universiti Kebangsaan Malaysia (HUKM) and Hospital Melaka. These images have 600 samples representing the 3 lesions (plaque:guttate:erythroderma), cropped and divided into training set of 468 samples with a proportion of 234:117:117 representing each lesion respectively. The testing set has 132 samples with 66:33:33 proportions. Just notice that all these sets are evenly distributed between plaque and non-plaque samples. These samples were then separated by three categorized color models which are the *RGB*, *YCbCr* and *HSV*. The samples were later clustered into two groups: plague and non-plague (comprised of guttate and erythroderma) and acts as inputs for fuzzy logic system. Initially, the *RGB* component color images were acquired using FinePix 6900 Zoom (FujiFilm) digital camera, with pixel resolution of 786x512. This size is sufficient for analysis, as all relevant details of the lesions are shown [18]. During the photo session, the camera was placed at a distance of one foot directly above the patient's skin.

### B. Pre-processing

Each image from the stored database was being filtered using median filter technique in order to remove any artifacts such as small white ellipse lines or dots. These artifacts can be considered as impulsive noise and may thus be reduced using a median filter given by [19]:

$$P_{med}(m,,n) = median\left\{P(m-k,n-1)\,\middle|\, -\frac{N_{med}-1}{2} \le k,\ l \le \frac{N_{med}-1}{2} \wedge 1 \le m-k \le m \wedge 1 \le n-1 \le N\right\} \quad (1)$$

where $N_{med}$ is an odd number that indicates the selected size of a two dimensional median filter. *P* represents all the color components. Note that only square median filter kernel was considered. After the filtering process, region of interest (ROI) which includes a sample of normal skin and three samples of lesion area were selected. Each image was carefully studied and observed by the dermatologists involved in this research. Once the regions have been identified by them, the images were cropped out sequentially with the normal skin first and followed by the other lesion sample. All samples were then been resized to a dimension of 256 by 256 pixel area for consistency in this research [14-16]. The differential method of gathering lesion sample color indices is defined as:

$$P_{hsv}(i,j) = [P_{hsv}\ lesion\ (i,j) - X_{hsv}\ skin] \quad (2)$$

where $X_{hsv}$ are the computed mean index for each color component of the selected ROI normal skin sample.

*HSV* parameters were derived non-linearly from *RGB* through the following mathematical conversion [15];

$$H = \begin{cases} \text{undefined} & \text{if } Max = Min \\ 60\,x\,\dfrac{G-B}{Max-Min} + 0 & \text{if } Max = R \text{ and } G \ge B \\ 60\,x\,\dfrac{G-B}{Max-Min} + 360 & \text{if } Max = R \text{ and } G < B \\ 60\,x\,\dfrac{B-R}{Max-Min} + 120 & \text{if } Max = G \\ 60\,x\,\dfrac{R-G}{Max-Min} + 240 & \text{if } Max = B \end{cases} \quad (3)$$

 ISBN: 978-1-61208-169-4

$$S = \begin{cases} 0 & \text{if } Max = 0 \\ 1 - \dfrac{Min}{Max}, & otherwise \end{cases} \quad (4)$$

$$V = Max[R, G, B] \quad (5)$$

*YCbCr* parameters were then created from the corresponding gamma adjusted RGB (red, green, blue) source using two defined Kb and Kr and the transformation are as follows:

$$Y = 0.299*R' + 0.587*G' + 0.114*B' \quad (6)$$

$$Cb = -0.168736*R' - 0.331264*G' + 0.5*B' \quad (7)$$

$$Cr = 0.5*R' - 0.418688*G' - 0.081312*B' \quad (8)$$

Here, *R'*, *G'* and *B'* are assumed to be nonlinear (gamma-adjusted) and has a nominal range from 0 to 1, with 0 representing the minimum intensity and 1 the maximum. The prime symbols denote the use of gamma adjustment. The resulting luma (*Y*) value will then have a nominal range from 0 to 1, and the chroma color difference(*Cb* and *Cr*) values will have a nominal range from -0.5 to +0.5 [16].

### C. Inference Test

Independent *t*-test was applied to obtain *p*-values that provide valuable information because it measures the amount of statistical evidence that supports the alternative hypothesis in this work as shown below.

Null hypothesis (no discrimination), $H_0$:

$$\mu_y - \mu_z = 0 \quad (9)$$

Alternative hypothesis (has discrimination), $H_1$:

$$\mu_y - \mu_z \neq 0 \quad (10)$$

Where $\mu_y$ ,$\mu_z$ is the population mean.

Statisticians translated *p*-value into 4 different descriptive terms, which are [17]:

- *p*-value <0.01:
  There is overwhelming evidence to infer that $H_1$ is true
- 0.01<*p*-value < 0.05:
  There is strong evidence to infer that $H_1$ is true
- 0.05<*p*-value < 0.1:
  There is weak evidence to infer that $H_1$ is true
- 0.1<*p*-value < 1.0:
  There is no evidence to infer that $H_1$ is true

### D. Fuzzy Inference Systems

Basically, fuzzy logic based in fuzzy inference systems (FIS) or Fuzzy-rule based systems as depicted in Figure 1 [20]. In this system a fuzzy fication interface transforms the input in degrees of match with linguistic values. Then a decision-making unit performs the inference operations on the rule base. Finally, a defuzzification which is a process of combining applicable fuzzy rules in order to assign a value to a given output interface transforms the fuzzy result of the interference process in a crisp output. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves all of the pieces that are described in the previous sections: membership functions, fuzzy logic operators, and *if then* rules. There are two types of fuzzy inference systems that can be implemented in the Fuzzy Logic Toolbox: Mamdani type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined. But, in this study, Mamdani type is selected due it more suitable for human input [20].

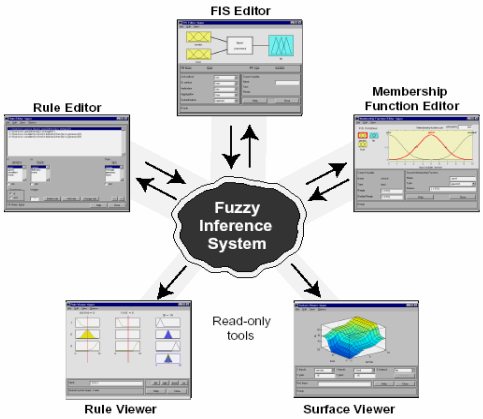


Figure1. Fuzzy inference systems (FIS)

### E. The FIS editor

The fuzzy inference system (FIS) Editor displays general information about a fuzzy inference system as shown in Figure 2. There is a simple diagram at the top that shows the names of each input variable on the left, and those of each output variable on the right. The sample membership functions shown in the boxes are just icons and do not depict the actual shapes of the membership functions [20].

 ISBN: 978-1-61208-169-4 

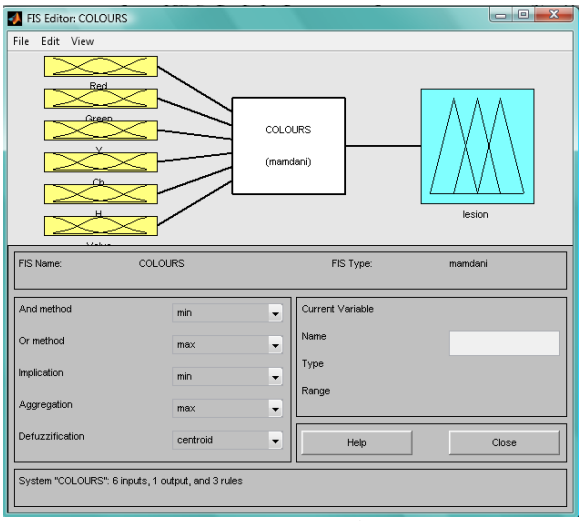


Figure 2. FIS Editor for colors

### F. Input and Output Membership Function

The fuzzy sets and the membership functions are defined in the following manner: if $X$ is a collection of objects, then a fuzzy sets $A$ in $X$ is defined as a set of order pairs [20], as in

$$A = \{x, \mu_A(x) | x \in X\} \quad (9)$$

From (7), $A$ represent a fuzzy set and $\mu_A(x)$ is a memberships function of $x$ in $A$.

### G. Fuzzy Rule Base

Fuzzy rule are a collection of linguistic statements that describe how the FIS should make a decision regarding classifying an input or controlling an output. This fuzzy logic was used production rules that consist of s precondition (IF-part) and a consequence (THEN-part) to represent the relation among the linguistic variables and to derive actions from inputs. There are six rules were defined for fuzzy logic system.

### H. Defuzzification

The choice of defuzzification method depends on the precision of the result [20]. There are five types of defuzzification methods where for this study, the Min of maximum (MoM) technique was chosen. This technique takes the output distribution and finds its mean of maxima to come up with one crisp number.

### I. Performance Indicators

Optimizations of the designed models for best learning coefficients were based on performance indicators such as sensitivity, specificity, diagnostic accuracy and receiver operating characteristic curve. Sensitivity and specificity are commonly used terms that generally describe the accuracy of a test. Sensitivity is a measure of the ratio or percentage of 'true' lesions (*TP*) and a positive diagnostic test result ($D+$). It represents the actual percentage of a 'true' lesion disease realized by a positive test result and is also known as true positive rate (*TPR*), defined as [14-16]:

$$Sensitivity: TPR = \frac{TP}{D+} \quad (13)$$

Specificity measures the ratio or percentage of 'false' lesions (*TN*) and with a negative diagnostic test result ($D-$). It actually represents the actual percentage of a 'false' lesion condition realized by a negative diagnostic test. Specificity is also termed as true negative rate (*TNR*) and is given as:

$$Specificity: TNR = \frac{TN}{D-} \quad (14)$$

The percentage for diagnostic accuracy (*DA*) refers to the percentage of samples that have been correctly classified or diagnosed, and have output values within the predefined threshold range for the respective output level. It can be derived as:

$$Accuracy: DA = \frac{TPR + TNR}{N} x100\% \quad (15)$$

## IV. Result and Discussion

Table I shows multiple comparison independent *t*-tests result to obtain *p*-values for quantitative measurement. It is observed that three color component; *B*, *S* and *Cb* has *p*-value >0.05 which implies that plaque cannot be discriminated from either both or one of the non-plaque lesions. Thus only six color components were considered for constructing the fuzzy model.

TABLE I PLAQUE INDEPENDENT *t*-TEST MULTIPLE COMPARISON

| Component | Non-plaque | Significant *p*-value |
|---|---|---|
| *R* | guttate | 0.00 |
| | erythroderma | 0.00 |
| *G* | guttate | 0.00 |
| | erythroderma | 0.00 |
| *B* | guttate | 0.00 |
| | erythroderma | 0.06 |
| *Y* | guttate | 0.00 |
| | erythroderma | 0.00 |
| *Cb* | guttate | 0.00 |
| | erythroderma | 0.00 |
| *Cr* | guttate | 0.501 |
| | erythroderma | 0.00 |
| *H* | guttate | 0.00 |
| | erythroderma | 0.00 |
| *S* | guttate | 0.22 |
| | erythroderma | 0.90 |
| *V* | guttate | 0.00 |
| | erythroderma | 0.00 |

Three inputs from each of these components for the model would then represent the *Low*, *Medium* and *High*

 ISBN: 978-1-61208-169-4 

level while the output has two levels for plaque and non-plaque. Ranges for each input membership function are taken from the outcome measurements of error plot obtained by the descriptive explorer SPSS with respect to *UCL* and *LCL*. The ranges for these inputs are shown in Table II. The number of training set samples is 468 and each sample's values were set as plaque boundary in membership function editor for FIS. Eventually, the triangular (trimf) has been used because it is the simplest way to describe the range of output. However, for input membership function, gaussian (gaussmf) has been used where it has more suitable curves that have advantage of being smooth and nonzero at all points.

TABLE II INPUT MEMBERSHIP FUNCTION FOR LOW, MEDIUM AND HIGH LEVEL

| Component | Low Level Range | | Medium level Range | | High level Range | |
|---|---|---|---|---|---|---|
| | *LCL* | *UCL* | *LCL* | *UCL* | *LCL* | *UCL* |
| *R* | -36.931 | -29.171 | -25.806 | -16.355 | 14.220 | 32.6249 |
| *G* | -53.276 | -46.785 | -27.776 | -20.371 | 5.942 | 18.173 |
| *Y* | -40.102 | -34.548 | -21.47 | -14.927 | 7.657 | 19.546 |
| *Cb* | 2.8027 | 4.1084 | 6.6155 | 8.222 | -0.8584 | 0.8737 |
| *H* | 0.8033 | 0.8611 | 0.6819 | 0.7384 | 0.5436 | 0.6799 |
| *V* | -31.731 | -24.955 | -8.7594 | -0.8617 | 20.0866 | 36.7455 |

Table III below shows the output ranges where it is divided into two categories; plaque and non plaque. Range of 0-5 represents plaque while range of 5.1-10, is for non-plaque. For example, if a new lesion sample is being applied to this designed fuzzy model, and has output range between 0-5, therefore that this sample is classified as plaque.

TABLE III OUTPUT RANGE OF MEMBERSHIP FUNCTION

| Output | Range |
|---|---|
| Plaque | 0.00 – 5.00 |
| Non-plaque | 5.10 – 10.00 |

Figure 3 describes the membership function for this investigation. The six yellow boxes shown on the left-hand side of the figure are the inputs membership function that have being applied to build the fuzzy system while the blue color box presents both targeted outputs. The membership function's value was obtained from previous input tables. The collection of linguistic statements was combined and a decision was made regarding classifying an input or controlling an output. In this system, fuzzyfication has transformed each input in terms of degree of matching with the respective linguistic values and later, an inference operation was performed by a decision making unit.

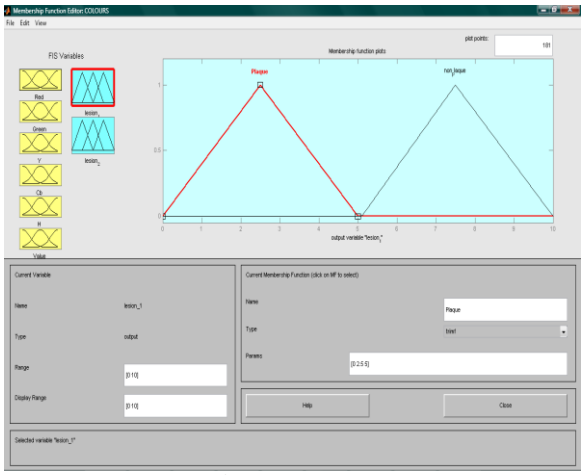

Figure3. Membership function creates based on range obtained

Table IV shows the performance indicators output produced by the fuzzy model. The testing set comprised of 132 samples of lesion tested in the fuzzy rule viewer. The percentage accuracy for plaque or TPR (sensitivity) is 72.72%, implying the model can recognize 48 samples out of 100 positively diagnosed samples. Only 18 samples would be falsely indentified as non-plaque. Alternatively when the model was tested with 100 negatively diagnosed as non-plaque, the percentage accuracy TNR (specificity) is 90.09%. This implies that the model has better capability to recognize non-plaque samples. Only 6 samples were falsely identified as positive. The overall diagnostic accuracy (DA) is calculated using equation (15) and for this fuzzy model, it is 81.82%.

TABLE IV OUTPUT AFTER TESTING USING FUZZY LOGIC

| Group | Tested Samples | Plaque | Non-plaque |
|---|---|---|---|
| Plaque | 66 | TP=48 (TPR=72.72%) | 18 |
| Non-plaque | 66 | 6 | TN=60 (TNR=90.09%) |

Finally, the performance of the designed fuzzy model is compared to ANN best model performance as described in Section I. Table V shows the comparison in terms of DA% and as a note, the number of training and testing samples used for designing and validating both models are the same. From the table, it is noted that the fuzzy model has higher percentage accuracy and outperformed ANN model by atleast 7%. This simulation results indicates that the fuzzy model is better in discriminating plaque lesion or otherwise non-plaque lesion.

TABLE V
PERFORMANCE COMPARISON BETWEEN FUZZY MODEL AND ANN BEST MODEL FOR INTELLIGENT PLAQUE LESION CLASSIFICATION

| | Fuzzy Model | ANN Model |
|---|---|---|
| Diagnostic Accuracy (%) | 81.82 | 75.00 |

 ISBN: 978-1-61208-169-4 

## V. CONCLUSION

The aim of this investigation is to design an intelligent fuzzy model that can discriminate plaque skin lesions from non-plaque or otherwise. This dermatological pre-diagnostic procedure utilized on lesion sample's color image processing and fuzzy logic algorithm. Combination of various color models, *i.e. RGB*, *YCbCr* and *HSV* were chosen because of widely being used for skin image study and also to be consistent with the previous work that used ANN as the pattern classifier. The front-end phase involved enhanced samples image processing for feature extraction in terms of differential mean pixel indices. These indices were statistically using independent *t*-test in order to identify the valid color components that have strong evidence for discriminating plaque from non-plaque group. The identified color components' parameters in terms of ranges of statistical measurements with respect to *UCL* and *LCL* were later used as the input membership function when designing the fuzzy model. While training the model with 432 samples, fuzzy fication has transformed each input in terms of degree of matching with the respective linguistic values and later, an inference operation was performed by a decision making unit where the targeted model output is to decide between plaque and non-plaque. Performance validation was conducted later on the fuzzy model with 132 samples of lesion and the result showed that it produces an overall accuracy of 81.82%. This proposed fuzzy model has also outperformed the best designed ANN model from previous work by at least 7% in terms of overall accuracy. The outcome of this experiment has concluded that fuzzy algorithm has better accuracy and can be recommended to be utilized in developing intelligent plaque psoriasis classification model.

## ACKNOWLEDGMENT

The authors would like to acknowledge Dr. Saadiah Sulaiman from Hospital Universiti Kebangsaan Malaysia (HUKM) and Dr. Roshidah Baba from Hospital Melaka (HM) for providing the psoriasis raw data images prior to the preparation of this project.

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