Supporting Information

Prediction of Dry Mouth Condition Using Radiomics Features from Tongue Diagnosis Image

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Radiomics Features

We evaluated a total of 462 tongue image features, which are extracted using first-order statistics and textural features. The textural features were calculated from three texture matrices which are the gray-level co-occurrence matrix (GLCM), gray-level run-length matrix (GLRLM), and gray-level size-zone matrix (GLSZM).

1. First-order statistics

First-order statistics characterize the distribution of pixel intensities within the tongue image. Let $\boldsymbol{X}$ denote the tongue image matrix consisting of $\boldsymbol{N}$ pixels. Let $\boldsymbol{P}$ represent the first order histogram, where $\boldsymbol{P(i)}$ is the fraction of pixels with intensity level $\boldsymbol{i}$ and $\boldsymbol{N_l}$ is the number of discrete intensity levels. 11 features were extracted as follow:

$$\text{Intensity average } (\bar{X}) = \frac{1}{N}\sum X(i)$$

$$\text{Energy} = \sum_{i=1}^{N} X(i)^2$$

$$\text{Entropy} = \sum_{i=1}^{N} P(i)\log_2 P(i)$$

$$\text{Kurtosis} = \frac{\frac{1}{N}\sum_{i=1}^{N}(X(i)-\bar{X})^4}{\left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X(i)-\bar{X})^2}\right)^2}$$

$$\text{Maximum value} = \max(\boldsymbol{X})$$

$$\text{Median value} = \text{the sample median of } \boldsymbol{X}\text{, or the } 50^{\text{th}} \text{ percentile of } \boldsymbol{X}$$

$$\text{Root mean square (RMS)} = \sqrt{\frac{\sum_i^N X(i)^2}{N}}$$

$$\text{Skewness} = \frac{\frac{1}{N}\sum_{i=1}^{N}(X(i)-\bar{X})^3}{\left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X(i)-\bar{X})^2}\right)^3}$$

$$\text{Standard deviation} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(X(i)-\bar{X})^2}$$

$$\text{Unifomity} = \sum_{i=1}^{N_l} P(i)^2$$

$$\text{Variance} = \frac{1}{N-1}\sum_{i=1}^{N}(X(i)-\bar{X})^2$$

2. *Textural features*

Gray-Level Co-occurrence Matrix (GLCM) based features

The features based on the Gray-Level Co-occurrence Matrix (GLCM) were originally described by Haralick et al. [1]. A normalized GLCM is defined as $\boldsymbol{P(i,j;\delta,\alpha)}$, a matrix of size $\boldsymbol{N_g \times N_g}$ that represents the second-order joint probability function of an image. In this matrix, the element $\boldsymbol{P(i,j;\delta,\alpha)}$ indicates the probability of the occurrence of intensity levels $\boldsymbol{i}$ and $\boldsymbol{j}$ in two pixels that are separated by a distance $\boldsymbol{\delta}$ of pixels in direction $\boldsymbol{\alpha}$. Here, $\boldsymbol{N_g}$ denotes the number of discreate intensity level in the image. Let: $P(i,j)$ be the normalized (i.e. $\sum P(i,j) = 1$) co-occurrence matrix, generalized for any $\boldsymbol{\delta}$ and $\boldsymbol{\alpha}$.

$p_x(i) = \sum_{j=1}^{N_g} P(i,j),\ p_y(j) = \sum_{i=1}^{N_g} P(i,j),$

$\mu_x(i) = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} iP(i,j),\ \mu_y(i) = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} jP(i,j),$

$\sigma_x^2 = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)(i-\mu_x)^2,\ \sigma_y^2 = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)\big(j-\mu_y\big)^2,$

$p_{x+y}(k) = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)\,,\ \ i+j=k,\ \ k = 2,3,\cdots,2N_g\,,$

$p_{x-y}(k) = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)\,, |i-j| = k,\ \ k = 0,1,\cdots,N_g-1\,,$

$\text{HX} = -\sum_{i=1}^{N_g} p_x(i)\log_2 p_x(i),\ \text{HY} = -\sum_{j=1}^{N_g} p_y(j)\log_2 p_y(j),$

$HXY1 = -\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)\ln\big(p_x(i)p_y(j)\big)\,,$

$HXY2 = -\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p_x(i)p_y(j)\ln\big(p_x(i)p_y(j)\big).$

$$\text{Average} = \frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i+j)P(i,j)}{N_g^2}$$

$$\text{Autocorrelation} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} ijP(i,j)$$

$$\text{Cluster prominence} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\left(i + j - \mu_x - \mu_y\right)^4 P(i,j)$$

$$\text{Cluster shade} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\left(i + j - \mu_x - \mu_y\right)^3 P(i,j)$$

$$\text{Cluster tendency} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\left(i + j - \mu_x - \mu_y\right)^2 P(i,j)$$

$$\text{Contrast} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}|i-j|^2 P(i,j)$$

$$\text{Correlation} = \frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} ijP(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y}$$

$$\text{Dissimilarity} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}|i-j|P(i,j)$$

$$\text{Homogeneity1 (Inverse Difference)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{P(i,j)}{1+|i-j|}$$

$$\text{Homogeneity2 (Inverse Difference Moment)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{P(i,j)}{1+|i-j|^2}$$

$$\text{Inverse Difference Moment Normalized (IDMN)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{P(i,j)}{1+\left(\frac{|i-j|^2}{N_g}\right)}$$

$$\text{Inverse Difference Normalized (IDN)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{P(i,j)}{1+\left(\frac{|i-j|}{N_g}\right)}$$

$$\text{Inverse variance} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{P(i,j)}{|i-j|}, i \neq j$$

$$\text{Difference average } \left(\mu_{x-y}\right) = \sum_{k=0}^{N_g-1} kp_{x-y}$$

$$\text{Difference entropy } = \sum_{i=0}^{N_g-1} p_{x-y}(i)\log_2\left(P_{x-y}(i)\right)$$

$$\text{Entropy (H)} = -\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P(i,j)\log_2 p(i,j)$$

$$\text{Informational measure of correlation 1} = \frac{H - HXY1}{\max(HX, HY)}$$

$$\text{Informational measure of correlation 2} = \sqrt{1 - e^{-2(HXY2 - H)}}$$

$$\text{Maximum probability} = \max[P(i,j)]$$

$$\text{Sum average (SA)} = \sum_{i=2}^{2N_g} iP_{x+y}(i)$$

$$\text{Sum entropy} = -\sum_{i=2}^{2N_g} P_{x+y}(i)\log_2 P_{x+y}(i)$$

$$\text{Sum variance} = \sum_{i=2}^{2N_g} (1 - SA)^2 P_{x+y}(i)$$

$$\text{Energy} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} [P(i,j)]^2$$

Gray-Level Run-Length Matrix (GLRLM) based features

Gray-level run-length matrix (GLRLM) based features, as described by Galloway et al. [2], quantify gray level runs within an image. A gray level run is defined as a sequence of consecutive pixels that share the same gray level value. In a gray level run length matrix $\boldsymbol{p(i,j|\theta)}$, the element at position ***(i,j)*** represents the number of times the gray level $\boldsymbol{i}$ occurs consecutively for $\boldsymbol{j}$ pixels in the direction specified by $\boldsymbol{\theta}$.

Let: ***p(i,j)*** be the ***(i,j)***-th entry in the given run-length matrix $\boldsymbol{p}$, generalized for any direction $\boldsymbol{\theta}$,

N_g the number of discrete intensity values in the image,

N_r the maximum run length,

$N_s = \sum_{i=1}^{N_g}\sum_{j=1}^{N_r} p(i,j),\ p_r(j) = \sum_{i=1}^{N_g} p(i,j),\ p_g(i) = \sum_{j=1}^{N_r} p(i,j),$

$N_p = \sum_{j=1}^{N_r} j\, p_r,\ p_n(i,j) = \frac{p(i,j)}{N_s},\ \mu_r = \sum_{i=1}^{N_g}\sum_{j=1}^{N_r} jp_n(i,j),\ \mu_g = \sum_{i=1}^{N_g}\sum_{j=1}^{N_r} ip_n(i,j).$

$$\text{Short Run Emphasis (SRE)} = \frac{1}{N_s}\sum_{j=1}^{N_r}\frac{p_r}{j^2}$$

$$\text{Long Run Emphasis (LRE)} = \frac{1}{N_s}\sum_{j=1}^{N_r} j^2 p_r$$

$$\text{Gray level Non} - \text{unifomity (GLN)} = \frac{1}{N_s}\sum_{i=1}^{N_g} p_g^2$$

$$\text{Gray level Non} - \text{unifomity Normalized (GLNN)} = \frac{1}{N_s^2}\sum_{i=1}^{N_g} p_g^2$$

$$\text{Run Length Non} - \text{uniformity (RLN)} = \frac{1}{N_s}\sum_{j=1}^{N_r} p_r^2$$

$$\text{Run Length Non} - \text{unifomity Normalized (RLNN)} = \frac{1}{N_s^2}\sum_{j=1}^{N_r} p_r^2$$

$$\text{Run Percentage (RP)} = \frac{N_s}{N_p}$$

$$\text{Low Gray Level Run Emphasis (LGRE)} = \frac{1}{N_s}\sum_{i=1}^{N_g} \frac{p_g}{i^2}$$

$$\text{High Gray Level Run Emphasis (HGRE)} = \frac{1}{N_s}\sum_{i=1}^{N_g} i^2 p_g$$

$$\text{Short Run Low Gray Level Emphasis (SRLGE)} = \frac{1}{N_s}\sum_{i=1}^{N_g}\sum_{j=1}^{N_r} \frac{p(i,j)}{i^2 j^2}$$

$$\text{Short Run High Gray Level Emphasis (SRHGE)} = \frac{1}{N_s}\sum_{i=1}^{N_g}\sum_{j=1}^{N_r} \frac{i^2 p(i,j)}{j^2}$$

$$\text{Long Run Low Gray Level Emphasis (LRLGE)} = \frac{1}{N_s}\sum_{i=1}^{N_g}\sum_{j=1}^{N_r} \frac{j^2 p(i,j)}{i^2}$$

$$\text{Long Run High Gray Level Emphasis (LRHGE)} = \frac{1}{N_s}\sum_{i=1}^{N_g}\sum_{j=1}^{N_r} i^2 j^2 p(i,j)$$

$$\text{Gray Level Variance (GLV)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_r} \left(i - \mu_g\right)^2 p_n(i,j)$$

$$\text{Run Length Variance (RLV)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_r} (i - \mu_r)^2 p_n(i,j)$$

$$\text{Run Entropy (RE)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_r} p_n(i,j|\theta)\log_2[p_n(i,j)]$$

Gray-Level Size-Zone Matrix (GLSZM) based features

Gray-Level size-zone matrix (GLSZM) based features, as described by Thibault et al. [3,4], characterize the quantity of homogeneous connected regions within an image plane based on specific size and intensity parameters. In the

GLSZM, the entry at position ***(i,j)***, denoted as ***p(i,j)***, represents the number of connected areas of gray-level ***i*** and size ***j***. Consequently, GLSZM features provide information about homogenous regions within the image.

Let: ***p(i,j)*** be the ***(i,j)***th entry in the given GLSZM ***p***,

N_g the number of discrete intensity values in the image,

N_z the size of the largest, homogeneous region in the region of interest,

$N_s = \sum_{i=1}^{N_g}\sum_{j=1}^{N_z} p(i,j),\ p_z(j) = \sum_{i=1}^{N_g} p(i,j),\ p_g(i) = \sum_{j=1}^{N_z} p(i,j),$

$N_p = \sum_{j=1}^{N_z} jp_z,\ p_n(i,j) = \frac{p(i,j)}{N_s},\ \mu_z = \sum_{i=1}^{N_g}\sum_{j=1}^{N_z} jp_n(i,j|\theta),\ \mu_g = \sum_{i=1}^{N_g}\sum_{j=1}^{N_z} ip_n(i,j|\theta).$

$$\text{Small Area Emphasis (SAE)} = \frac{1}{N_s}\sum_{j=1}^{N_z}\frac{p_z}{j^2}$$

$$\text{Large Area Emphasis (LAE)} = \frac{1}{N_s}\sum_{j=1}^{N_z} j^2 p_z$$

$$\text{Intensity Non} - \text{unifomity (IN)} = \frac{1}{N_s}\sum_{i=1}^{N_g} p_g^2$$

$$\text{Intensity Non} - \text{unifomity Normalized (INN)} = \frac{1}{N_s^2}\sum_{i=1}^{N_g} p_g^2$$

$$\text{Size} - \text{Zone Non} - \text{uniformity (SZN)} = \frac{1}{N_s}\sum_{j=1}^{N_r} p_r^2$$

$$\text{Size} - \text{Zone Non} - \text{unifomity Normalized (SZNN)} = \frac{1}{N_s^2}\sum_{j=1}^{N_z} p_z^2$$

$$\text{Zone Percentage (ZP)} = \frac{N_s}{N_p}$$

$$\text{Low Intensity Emphasis (LIE)} = \frac{1}{N_s}\sum_{i=1}^{N_g}\frac{p_g}{i^2}$$

$$\text{High Intensity Emphasis (HIE)} = \frac{1}{N_s}\sum_{i=1}^{N_g} i^2 p_g$$

$$\text{Low Intensity Small Area Emphasis (LISAE)} = \frac{1}{N_s}\sum_{i=1}^{N_g}\sum_{j=1}^{N_z}\frac{p(i,j)}{i^2 j^2}$$

$$\text{High Intensity small Area Emphasis (HISAE)} = \frac{1}{N_s}\sum_{i=1}^{N_g}\sum_{j=1}^{N_z}\frac{i^2 p(i,j)}{j^2}$$

$$\text{Low Intensity Large Area Emphasis (LILAE)} = \frac{1}{N_s}\sum_{i=1}^{N_g}\sum_{j=1}^{N_z}\frac{j^2 p(i,j)}{i^2}$$

$$\text{High Intensity Large Area Emphasis (HILAE)} = \frac{1}{N_s}\sum_{i=1}^{N_g}\sum_{j=1}^{N_z} i^2 j^2 p(i,j)$$

$$\text{Intensity Variance (IV)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_z}\left(i-\mu_g\right)^2 p_n(i,j)$$

$$\text{Size} - \text{Zone Variance (SZV)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_z}(i-\mu_z)^2 p_n(i,j)$$

$$\text{Zone Entropy (ZE)} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_z} p_n(i,j)\log_2[p_n(i,j)]$$

Reference

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