

# Classification of Tongue - Glossitis Abnormality

Ashiqur Rahman, Amr Ahmed, Shigang Yue

**Abstract**—This manuscript presents an approach to classify tongue abnormality related to Diabetes Mellitus (DM) following Western Medicine (WM) approach. Glossitis abnormality is one of the common tongue abnormalities that affects patients who suffer from Diabetes Mellitus (DM).

The novelty of the proposed approach is attributed to utilising visual signs that appear on tongue due to Glossitis abnormality caused by high blood sugar level in the human body. The test for the blood sugar level is inconvenient for some patients in rural and poor areas where medical services are minimal or may not be available at all. To screen and monitor human organ effectively, the proposed computer aided model predicts and classifies abnormality appears on the tongue or tongue surface using visual signs caused by the abnormality. The visual signs were extracted following a logically formed medical approach, which complies with Western Medicine (WM) approach. Using Random Forest classifier on the extracted visual tongue signs, from 572 tongue samples for 166 patients, the experimental results have shown promising accuracy of 95.8% for Glossitis abnormality.

**Index Terms**—tongue classification; random forest, machine learning, western medicine (wm).

## I. INTRODUCTION

**P**ERSONAL Health Monitoring (PHM) is becoming the part of our daily life due to affordable portable devices with high processing power and low cost sensors. The portable device applications are being used to allow people to self-monitor to improve their health.

The rapid increase of the global population is predicted to increase the pressure on healthcare systems of many countries and would potentially to outstrip the available medical recourses [1]. During the last decade, the human life expectancy has been increased rapidly due to improved medical care. Because of that, ageing of the population trend that has been going on for last few years, will be continuing for next few years [2]. The diseases associated to the ageing groups can be considered as chronic. It would be essential to monitor these diseases to control the vital issues as these diseases are associated with young groups too. There are chronic diseases that are required to be monitored day to day basis such as Diabetes, heart disease, pregnancy stages, etc. Recently compiled data showed that 150 millions people are suffering from Diabetes worldwide, which can be doubled by the year 2025 [3].

Manuscript received on March 06, 2017, revised on April 10, 2017.

Ashiqur Rahman, is a Research Student at School of Computer Science, University of Lincoln, Brayford Pool, Lincoln LN6 7TS, United Kingdom, e-mail: arahman@lincoln.ac.uk, ResearcherID: G-5435-2017.

Dr. Amr Ahmed, is a Faculty Member at School of Computer Science, University of Lincoln, Brayford Pool, Lincoln LN6 7TS, United Kingdom, email: aahmed@lincoln.ac.uk.

Professor Shigang Yue, is a Faculty Member at School of Computer Science, University of Lincoln, Brayford Pool, Lincoln LN6 7TS, United Kingdom, email: syue@lincoln.ac.uk.

### A. Diabetic Tongue

Diabetes Mellitus (DM) or commonly known as Diabetes, is a group of metabolic diseases in which high blood sugar stays in human body over a prolonged period of time [3]. It manifests in the form of organ infection, polyuria, polydipsia, weight loss, fatigue, retinal problems, skin infections and slow healing process of skin damages [4].

Tongue diagnosis is one of the most common diagnoses in Traditional Chinese Medicine (TCM) [5]. But in the Western Medicine (WM), Tongue is an integral part of systematic diagnosis process for various diseases in Clinical Pathology [6], [7]. This research has looked into tongue features such as tongue size, shape, colour, textures and changes that occur if a patient develops Diabetes Mellitus (DM).



Fig. 1: Glossitis abnormality affected tongue.

Glossitis abnormality is one of the common abnormalities that occurs due to Diabetes Mellitus (DM) [8]. It is a condition that is caused by swelling and loss of lingual papillae [9]. The common signs and symptoms are changes of tongue colour, loss of tissue, swelling and difficulties to swallow food.

The paper is organised as follows; Section II presents the related research from the body of literature. Section III presents the proposed work, which includes Visual Signs Extraction and Classification. Section IV presents with experimental results and discussion while Section V summarises the findings of the study through the conclusion.

## II. RELATED WORK

Tongue diagnosis is one of the most important diagnoses in Traditional Chinese Medicine (TCM) and it has been used widely for thousands of years for clinical analysis and application in China. Its inexpensiveness and simplicity make the tongue diagnosis very competitive to develop a computer based diagnosis system. Recently, there is a trend to utilise image processing and pattern recognition technology in the aid of quantitative analysis for tongue image diagnosis. However tongue diagnosis is usually subjective, qualitative and always difficult to automate the whole process [10].

A TCM based tongue classification was introduced in, 120 tongue samples were segmented using a combination of the watershed transform and an active contour model (ACM) [5]. 21 properties from tongue substances and coating were derived from the tongue that contributed to 24 tongue classes for the classification. Five different machine learning classifiers were applied including ID3, J48, Naive Bayes, BayesNet and SVM on 457 instances. An accuracy of 96.03% was achieved using SVM with leave-out evaluation technique. The processes and techniques were used to extract features from tongue followed the TCM, but TCM is not sufficiently approved in the Western Medicine (WM).

A Bayesian diagnosis model of TCM symptoms was developed using the Hypertension Epidemiological Syndrome databases to build the Tree Augmented Naive Bayes models [11]. The research focused on signs and symptoms that required input from a patient, resulting to build a semi-automated system. The Bayesian network model achieved an accuracy of 72.11%, without prior knowledge, where the accuracy of the model was increased to 78.55% with prior knowledge.

In yet another quantitative study on the tongue characters in TCM physique was introduced following the classification and decision of TCM physique that consists of four tongue categories and it was published by the China Association of Chinese Medicine in China [12]. The colour features of the tongue samples were extracted using HSV colour space, the texture features of the tongue samples were extracted using statistical analysis method of grey level co-occurrence matrix and the teeth were identified using Graham's scan to find convex hull technique from the tongue samples. The extracted features from tongue samples were accepted by the TCM experts in China and the feasibility of the tongue diagnosis was objectified in TCM.

After surveying published papers, the majority of the researchers worked on Traditional Chinese Medicine (TCM) and proposed systems to detect various human health issues following Traditional Chinese Medicine (TCM). But the problem of TCM is that the TCM is not sufficiently approved in Western Medicine (WM). Majority of the researchers did not attempt to develop a system following Western Medicine (WM) approach, which can be tested and verified by the conventional medical tests in practice developed by Western Medicine (WM).

### III. PROPOSED WORK

The main goal is to develop a model to classify abnormal tongues affected by the Glossitis abnormality. Also, develop a systematic process to extract visual signs from tongue samples in collaboration with medical experts from Western Medicine (WM) domain.

#### A. Visual Signs Extraction

The first stage of this research is to extract visual signs from tongue samples. We only considered tongue signs, which are defined in Western Medicine (WM) and are not part of Traditional Chinese Medicine (TCM). We decided to extract visual signs from tongue samples and verified the tongue signs by medical experts to confirm that these signs

are related to Glossitis abnormality. We divided extracted visual signs from tongue samples into two categories, which are listed below:

- 1) Shared Features.
- 2) Distinctive Features.

1) *Shared Features*: Abnormal tongues have common features and those features belong to common abnormalities, not only Glossitis abnormality.

- Swelling: Infected tongue appears to be swollen.
- Dehydration: Looks dry compared to a normal tongue.
- Betel Nut Stained: A personal habit to take Betel leaves with Betel nut [13], [14].
- Tongue Colour: We defined 8 (eight) colours for normal tongue and abnormal tongue.

2) *Distinctive Features*: Many features distinctively belong to Glossitis abnormality that define the Glossitis abnormality. The distinctive features are listed below:

- Erythematous: Abnormal redness due to capillary congestion.
- Depapillation: Smooth tongue surface due to lingual papillae.
- Atrophic: Lose of tissue and creates shallow or deep ulceration.
- Rhomboid: Rhombus shape appears on tongue due to lose of tissue.

Both shared features and distinctive features were extracted with the help of two Endocrinologists and a General Practitioner (GP) from Western Medicine (WM) domain.

#### B. Classification

The second and final stage of this research is the Classification, this is to construct the computer aided model, where the input is the extracted set of visual signs from the previous stage. The goal of the classification stage is to apply a learning-based approach considering the input for the purpose of the classification. After extraction of the visual signs from tongue samples, Naive Bayes [15] and Random Forest [16] classifiers were applied to classify the tongue abnormality.

## IV. EXPERIMENTAL RESULTS

This section contains the experimental models for Glossitis abnormality. The training data used for the models is completely separate than the test data and the test data was not part of the training data. The experiments focused on constructing models for Glossitis abnormality using extracted visual signs from the tongue samples.

#### A. Experiment Setup

We obtained the medical data of 166 patients to use it as training data. The medical experts diagnosed and identified the Glossitis abnormality on tongue samples and the total number of Glossitis abnormality cases in training data are:

- **Glossitis abnormality in training data:**
  - Glossitis: 63 cases.
  - Non-Glossitis: 103 cases.

We also obtained medical data of 50 patients to use it as test data and the total number of Glossitis abnormality affected cases in test data are:

**Glossitis abnormality in test data:**

- Glossitis: 23 cases.
- Non-Glossitis: 27 cases.

The tongue colours extracted from the tongue samples are Pink (P), White (W), Pale (Pa), Blue (B), Purple (Pu), Red (R), Darker Red (D.R) and Grey (G) according to Western Medicine (WM) approach.

We assigned binary values to each tongue colour that can be used to identify uniquely for any combination of the tongue colours for a tongue, as depicted in TABLE I.

TABLE I: Binary values for tongue colours.

Tongue colour								
P	W	Pa	B	Pu	R	D.R	G	Colour
1	0	0	0	0	0	0	0	P
0	1	0	0	0	0	0	0	W
0	0	1	0	0	0	0	0	Pa
0	0	0	1	0	0	0	0	B
0	0	0	0	1	0	0	0	Pu
0	0	0	0	0	1	0	0	R
0	0	0	0	0	0	1	0	D.R
0	0	0	0	0	0	0	1	G

We also assigned categorical values (Yes, No) to each extracted visual feature from Glossitis abnormality affected tongue samples to achieve the best possible model performance, as depicted in TABLE II.

TABLE II: Categorical values for tongue visual features.

Name of feature	Affirmative value	Negative value
Swollen	Yes	No
Erythematous	Yes	No
Depapillation	Yes	No
Atrophic	Yes	No
Rhomboid	Yes	No
Dehydrated	Yes	No
Betel Nut Stain	Yes	No

The extracted visual signs with assigned values from the tongue samples were used as input for learning-based approaches to classify the tongue abnormality.

**B. Evaluation and Result**

This section presents the evaluation and result for the model and its classification performance in our proposed model.

We constructed the Naive Bayes and Random Forest models by training both models with the extracted visual tongue signs from 166 cases as their input. The correctly and incorrectly classified tongue samples from both models, on the test data, are listed below:

TABLE III: Naive Bayes vs. Random Forest classification.

Name of Model	Correctly classified	Incorrectly classified	Total Cases
Naive Bayes	45	5	50
Random Forest	47	3	50

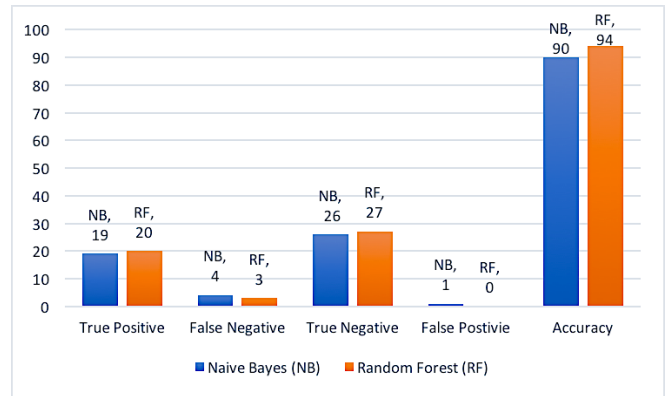


Fig. 2: Naive Bayes vs. Random Forest classification.

To evaluate the performance of the classification, several standard measures were used, as defined below:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (2)$$

$$Specificity = \frac{TN}{(TN + FP)} \quad (3)$$

The Accuracy, Sensitivity and Specificity from Naive Bayes and Random Forest models, on the test data, are listed below:

TABLE IV: Random Forest vs. Naive Bayes performance measures.

Name of model	Accuracy	Sensitivity	Specificity
Naive Bayes	90%	83%	96%
Random Forest	94%	87%	100%

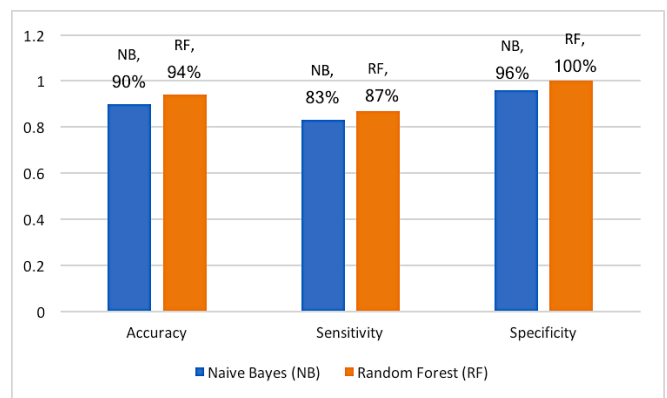


Fig. 3: Random Forest vs. Naive Bayes performance measures.

The Random Forest model classified more abnormal tongues than Naive Bayes model and achieved higher Accuracy, Sensitivity and Specificity compared to Naive Bayes model. The authors verified the correctly classified tongue samples with medical experts. The proposed model classified tongues affected by Glossitis abnormality and the affected tongues belong to patients who are suffering from Diabetes Mellitus (DM).

## V. CONCLUSION

This paper proposed a novel way to classify a tongue abnormality related to Diabetes Mellitus (DM). The authors developed a systematic process to select, identify and extract visual signs from a abnormal tongue in collaboration with medical experts from Endocrinology and General Medicine field in Western Medicine (WM). More importantly, the model achieved high accuracy rate of 94% for Glossitis model. The Glossitis model achieved 95.8% accuracy on the training data used as test data. The accuracy of the Random Forest model for Glossitis abnormality on the test data are similar to the gold standard accuracy on the training data.

### A. Future Work

In this paper, we proposed a computer aided model that was constructed using extracted visual signs from tongue samples. We aim to improve the model and add more abnormalities in near future. With real world application, a patient would use a portable device (i.e., mobile phone with a camera, tablet with a camera, etc) to capture an image, segment the image, extract features, classify and characterise the tongue sample into one or more abnormalities without the need of inputs from medical personnel. Using mobile or portable devices, it has a number of issues to be addressed including lighting conditions, relative distances and viewing point, to name just a few.

## ACKNOWLEDGMENT

The authors would like to thank Professor (Dr.) Farid Uddin, Dr. Md. Habibur Rahman and Dr. Abdul Hannan for the medical data, their invaluable opinions and collaboration with Digital Contents Analysis, Production, and Interaction (DCAPI) research group. We are grateful to Dr. Md. Habibur Rahman for his guidance to develop a systematic process to identify tongue features, reviewing each tongue sample to extract visual signs and the diagnosis of tongue abnormalities.

We would also like to thank Mrs. Ghada Mohamed (Acupuncturist Practitioner) for the chat that sparked the idea of the project and for her support all the way through. Thanks to Dr. Fanyi Meng, the Program Leader for Acupuncture undergraduate course in Lincoln College for the further discussions on the idea at its initial stage.

## REFERENCES

- [1] E. M. Agree, V. A. Freedman, J. C. Cornman, D. A. Wolf, and J. E. Marcotte, "Reconsidering substitution in long-term care: When does assistive technology take the place of personal care?" *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, vol. 60, no. 5, pp. S272–S280, 2005. [Online]. Available: <http://psychsocgerontology.oxfordjournals.org/content/60/5/S272.abstract>
- [2] I. Mohamed, A. Misra, M. Ebling, and W. Jerome, "Context-aware and personalized event filtering for low-overhead continuous remote health monitoring," in *2008 International Symposium on a World of Wireless, Mobile and Multimedia Networks*, June 2008, pp. 1–8.
- [3] W. H. O. (WHO), "Diabetes mellitus," 2017. [Online]. Available: <http://www.who.int/mediacentre/factsheets/fs138/en/>
- [4] D. L. Kasper, A. S. Fauci, and S. L. Hauser, *Harrisons principles of internal medicine*, 19th ed. New York, NY, United States: McGraw-Hill Professional, 05 2015, vol. 1, 2.
- [5] S. C. Hui, Y. He, and D. T. C. Thach, "Machine learning for tongue diagnosis," in *2007 6th International Conference on Information, Communications Signal Processing*, Dec 2007, pp. 1–5.
- [6] N. N. Bhandare, M. S. Keny, R. P. Nevrekar, and P. N. Bhandare, "Diabetic tongue - could it be a diagnostic criterion?" *Journal of Family Medicine and Primary Care*, vol. 3, no. 3, pp. 290–291, Jul-Sep 2014. [Online]. Available: <http://www.ncbi.nlm.nih.gov/pmc/articles/PMC4209693/>
- [7] H. Antkiewicz, J. Sadlak-Nowicka, and B. Szumska-Tyrzyk, "Pathologic changes in the tongue as signs of systemic diseases," *US National Library of Medicine*, 2004. [Online]. Available: <https://www.ncbi.nlm.nih.gov/pubmed/15181750>
- [8] M. Goregen, O. Miloglu, M. C. Buyukkurt, F. Caglayan, and A. E. Aktas, "Median rhomboid glossitis: A clinical and microbiological study," *European Journal of Dentistry*, vol. 5(4), pp. 367–372, 10 2011.
- [9] J. Ghabanchi, A. A. Tadbir, R. Darafshi, and M. Sadegholvad, "The prevalence of median rhomboid glossitis in diabetic patients: A case-control study," *US National Library of Medicine*, vol. 13, no. 7, 07 2011. [Online]. Available: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3371980/>
- [10] W. Zuo, K. Wang, D. Zhang, and H. Zhang, "Combination of polar edge detection and active contour model for automated tongue segmentation," in *Image and Graphics (ICIG'04), Third International Conference on*, Dec 2004, pp. 270–273.
- [11] W. w. Ouyang, X. z. Lin, Y. Ren, Y. Luo, Y. t. Liu, J. m. Yuan, A. h. Ou, and G. z. Li, "Tcm syndromes diagnostic model of hypertension: Study based on tree augmented naive bayes," in *2011 IEEE International Conference on Bioinformatics and Biomedicine Workshops (BIBMW)*, Nov 2011, pp. 834–837.
- [12] J. Zhang, G. Hu, and X. Zhang, "Extraction of tongue feature related to tcm physique based on image processing," in *2015 12th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP)*, Dec 2015, pp. 251–255.
- [13] C. Sui and A. Lacey, "Asia's deadly secret: The scourge of the betel nut," 03 2015. [Online]. Available: <http://www.bbc.co.uk/news/health-31921207>
- [14] H. Whiteman, "Nothing to smile about: Asia's deadly addiction to betel nuts," 11 2013. [Online]. Available: <http://edition.cnn.com/2013/11/04/world/asia/myanmar-betel-nut-cancer/>
- [15] G. H. John and P. Langley, "Estimating continuous distributions in bayesian classifiers," in *Proceedings of the Eleventh Conference on Uncertainty in Artificial Intelligence*, ser. UAI'95. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1995, pp. 338–345. [Online]. Available: <http://dl.acm.org/citation.cfm?id=2074158.2074196>
- [16] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001. [Online]. Available: <http://dx.doi.org/10.1023/A:1010933404324>