SUPPLEMENTARY INFORMATION

Oral Squamous Cell Carcinoma Diagnosed from Saliva Metabolic Profiling

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Materials and Methods

Saliva Collection and Pretreatment. All of the 373 saliva samples were collected from the Department of Oral and Maxillofacial Surgery, Nanjing Stomatological Hospital. The clinical information on OSCC patients, PML patients, and HC volunteers were summarized in **Table S1**. These volunteers diagnosed to be complicated with other oral diseases (e.g., chronic periodontitis). Besides, saliva collected from another nine healthy volunteers were also treated as the negative quality control in pattern recognition of metabolic profiling and method validation. The saliva collection was approved by the medical ethics committee of the Nanjing Stomatology Hospital. All patients were informed and signed consent forms. To avoid diet interferences, mouth rinsing with ultrapure water was required before saliva collection. Oral hygiene products (e.g., toothpaste) were also not allowed for use before 1.0 h prior to sample collection. Whole saliva (500 μ L) was harvested into an EP tube without exogenous stimulus. After centrifugation at 5000 rpm for 3 min, the supernatant was transferred and saved at -80 °C until use. Additionally, to confirm the discovered metabolites at the *in situ* level, tumor tissues collected from 22 OSCC patients were cryo-sectioned (15 μm) for DESI-MSI confirmation.

CPSI-MS and DESI-MSI method. For CPSI-MS analysis, the general procedure was according to that previously reported. Briefly, the 3 μL saliva (spiked with 3-cholorophenylalanine as internal standard) was first micropipetted onto the conductive polymer tip, which was tuned by XYZ positioner and set at 8.0 mm distance away from the MS inlet. When the saliva was dried to form a spot, methanol-water (7:3, v/v , 3 μ L) was used as the spraying solvent to dissolve endogenous metabolites in the dried spot. When the + 4.5 kV high voltage was applied onto the conductive polymer by a copper alligator clip, a plume of charged microdroplets will be sprayed and carry the components into the mass spectrometer. The LTQ Orbitrap Velos mass spectrometer (Thermo Scientific) was employed for the ambient MS analysis task. The full scan mode was used for untargeted metabolic profiling within the range of *m/z* 50-500 under positive mode. The MS capillary temperature was set at 275 °C with the S-lens voltage set at 55 V. The automatic gain control was set at 3E6 with the maximum injection time set at 400 ms.

 For tissue imaging, a commercial 2D DESI system (Prosolia, Inc, US) was employed in the positive ion mode with all of the other MS parameters same as above. Acetonitrile-water (7:3, v/v) was used as the spray solvent with the flow rate set at 2.0 μL/min under nebulizer gas pressure of 1.0 MPa. The impact angle between sprayer head (+4.0 kV applied) and substrate was 55°. The height of sprayer tip and the distance from tip to transport tube were all set at 4.5 mm.

CPSI-MS and DESI-MSI Data Preprocessing. The Xcalibur software was employed for generating average mass spectra and converting a batch of raw data files into cdf files. The ion's m/z within ± 0.005 Da mass tolerance will be defined with one mass bin. Only the mass bin that was successfully detected among more than 30 % of samples was used for data matrix construction. Self-written MATLAB 2019a (Mathworks, US) script was used to automatically extract average peak intensities of MS scans in the sample's time window, constructing the data matrix which consisted of m samples (rows) and n metabolite ions (columns). To eliminate the influence of signal response fluctuation on the statistical analysis, both total ion current (TIC) and internal standard ion intensity (*m/z* 222.03, [M+Na] +) of each sample's average mass spectrum can be the optional choice for intensity normalization to achieve the good modeling performance. The matrix was transferred through natural logarithm and then standardized to be centered at zero with standard deviation scaled at one, ruling out the magnitude's biasing influence on the classification. As for DESI-MSI data, Massimager (Chemmind Technologies Co., Ltd, China) and a self-programmed MATLAB script was used for ion image reconstruction and spatial segmentation.

Machine Learning. The samples were divided into two batches for CPSI-MS data acquisition separately within two different periods. The collected data was split into 193 samples in the first batch for training and 180 samples in the second batch for validation. The first batch contained saliva from 65 healthy contrast volunteers (HC), 64 patients with premalignant lesions (PML), and 64 oral squamous cell carcinoma patients (OSCC). The second batch contained saliva from 60 HC, 60 PML, and 60 OSCC cases. We first trained the model via cross-validation (20-folds) on the training set and externally validate the model performance on the held-out 5% test set.

A total of 627 common peaks were extracted from two batches (training and validation datasets) of saliva mass spectra. The MATLAB2019a was employed for developing machine learning models to differentiate the HC, PML, and OSCC cases. The in-built "classification learner" and "regression learner" APPs were employed for investigate and compare the model performances in fitting and generalization. The investigated classification models included decision tree (DT), discriminant analysis (DA), support vector machine (SVM), K nearest neighbor (KNN), naïve Bayesian classifier (NB). Besides, "neural net pattern recognition" APP was also used to build the artificial neural network classification model. The in-built "Lasso" function in MATLAB was used to establish the Lasso regression model. The number of crossvalidation was set at 20 folds using the in-built "crossvalind" function. The data matrix of the training and validation datasets as well as the related self-written code and functions have been uploaded into the open-source platform OSF. All of these files can be accessed from the following linkage: [https://osf.io/nv32d/.](https://osf.io/nv32d/)

The accuracy and mean squared error (MSE) were used to evaluate the performance of the different machine learning models. Receiver operating curve (ROC) analysis was carried out using Graphpad Prism to evaluate the diagnostic metrics including area under curve (AUC), specificity, and sensitivity. Confusion matrix was used to display the classification results for the training and validation datasets.

Dynamic Simulation. After finishing the machine learning training and validation, the Lasso model was deployed under the Simulink platform to simulate the on-line automated screening of the HC, PML, and OSCC population. After the conversion of acquired batch raw files into cdf format, the feature ions intensities of each MS scan were automated extracted, transformed, and input into the deployed Lasso model to give the instant diagnosis result. The in-built functional blocks such as "from workspace," "sumover," "matrix multiply," "sum," "constant," "scope," and "switch" in Simulink platform were organized to stimulate the dynamic Lasso recognition model. More details about the configuration are shown in **Figure S10**.

Statistical Analysis. Univariate analysis was first implemented to search for significantly changed metabolite ions among HC, PML, and OSCC groups using student t test. The P values were checked and adjusted with the false discovery rate (FDR) using Benjamini-Hochberg method. The ions were picked out if the fold change was over 2.0 or less than 0.5 ($P < 0.05$ and FDR<0.1). For pattern recognition of different groups, SIMCA-P (Umetrics, Umea, Sweden) was used for (orthogonal) partial least squares discriminant analysis ((O)PLS-DA) of metabolic profiles. Variables with importance in projection (VIP) larger than 1.5 were considered to make a high contribution to the classification. In addition, OPLS-DA were also used to investigate the inter-time, interday, and individual variation of the metabolic profile, as well as the influence of diet on sample classification.

Metabolite Identification and Metabolic Pathway Searching. The significantly changed ions in HR-MS were first identified through database searching from HMDB [\(http://hmdb.ca/\)](http://hmdb.ca/). To achieve the elemental composition and possible list of endogenous metabolites, the relative error of exact *m/z* value was limited to 5.0 ppm. The type of ion adducts were limited to $[M+H]^+$, $[M+Na]^+$, $[M+K]^+$, $[M-H_2O+H]^+$, [M+2Na-H]⁺, [M+2K-H]⁺, [M+NH4]⁺ under positive mode. The fragment ions produced under CID-MS2 were also used to assign the exact structure for a specific metabolite. The CID-MS2 fragmentation patterns were compared either with the standards, or matched with the self-built CID spectra collections, or the standard MS2 spectra in the metabolomics database (HMDB). The identified metabolites of interest were put into the open-source platform, MetaboAnalyst [\(https://www.metaboanalyst.ca\)](https://www.metaboanalyst.ca/), to search for these altered metabolic pathways.

Comparison to Flow Injection-ESI and Paper Spray Ionization-MS. Practically, flow injection (FI)-ESI consumes more biological fluid samples ($20^{\circ}500 \mu L$) or it dilutes the biofluid for filling up the syringe. Direct injection of biofluid will seriously foul the tubing system and cause inter-samples cross talk unless the syringe and tubing system are thoroughly washed after each assay. This limits its practical use in large scale sample tests. The saliva will strongly suppress the generation of electrospray at the ESI capillary outlet due to its strong viscosity and surface tension. In comparison, CPSI-MS utilizes self-conductive materials, and only consumes no more than several μL of sample on the tip. The materials are cheap and can be either disposable or repeatedly used after simple wiping with wet, dust-free tissue. Thus, CPSI-MS is very suitable for large scale metabolomics screening. Compared to paper spray ionization (PSI), we have discussed this before at length[\(1\)](#page-5-0). The signal intensity for polar or hydrophilic species tends to be at least 20 to 100 fold higher in CPSI-MS than those in the PSI-MS. We have added the above information to the supporting information.

1. Song XW, Chen, H., Zare, R.N. (2018) Conductive Polymer Spray Ionization Mass Spectrometry for Biofluid Analysis. Anal Chem 90:12878-12885.

Figure S1. Salivary metabolic profiling of different batches and groups with OPLS-DA: (A) metabolic profiling of first batch of 193 saliva cases as the discovery dataset; (B-D) metabolic profiling of three sub-batches of saliva cases over successive three days; (E) saliva metabolic profiling of 180 validation cases; and (F) metabolic profiling of total 373 saliva cases.

Figure S2. Visual display of the mass spectra of all saliva cases acquired with CPSI-MS to evaluate the repeatability of CPSI-MS results. (A) First batch of 193 cases as the discovery dataset. (B) Second batch of 180 cases as the validation dataset. The obviously changed MS peaks are indicated by arrows. The annotated peaks were ones which can be identified as cadaverine (peak No.83), glycerol (No.97), 5-aminopentanoate (No. 100), proline (No. 167), betaine (No. 172), arginine (No. 214), glucose (No. 306), phosphorylcholine (No.379), and MG(18:0/0:0/0:0) (No.606). (C) Pearson correlation coefficients.

Figure S3. Monitoring and quality control of the salivary metabolic data acquisition with CPSI-MS. (A) Representative mass spectrum of saliva spiked with internal standard (IS) 3 cholrophenylalanine (IS peaks at [M+Na] ⁺ *m/z* 222.03 and [M+K] ⁺ *m/z* 238.00). (B) The intra-day and inter-day variation of IS peak ions in 18 QC saliva samples. (C) Variation of internal standard peak ([M+Na]⁺ *m/z* 222.0383) spiked in the tested and quality control saliva samples. The IS ion intensities fall into the range of mean±SD (3.34E6±2.5E6). The QC samples came from the unique IS-spiked pooling aliquot collected from 20 normal contrast saliva.

Figure S4. Investigation of CPSI-MS/OPLS-DA robustness to the (A) dietary, (B) individual, (C) intertime, and (D) inter-day variation in salivary components. HC represents healthy contrast saliva collected from eight different persons. The collection was set at fixed date and time. Mouth rinsing with ultrapure water was required before saliva collection to avoid diet interferences. Oral hygiene products (e.g., toothpaste) were also not allowed for at least 1.0 h prior to sample collection.

Figure S5. Top 10 metabolites identified according to exact fragment ion assignments given by CID-MS/MS.

Figure S6. Representative metabolites identified according to exact fragment ion assignments given by CID-MS/MS.

Figure S 6 (continued).

Figure S6 (continued).

Figure S7. Venn diagrams of mutual ions or metabolites among different batches or groups. The mutual ions (A) and metabolites (B) with significant changes during premalignant progression that were discovered by the first and second batches. The mutual ions (C) and metabolites (D) with significant changes during malignant progression that were discovered by the first and second batches. (E) The mutual ions which were found significantly changed both in premalignant and malignant stages. (F) The mutual metabolites which were found significantly changed both in premalignant and malignant stages.

Figure S8. Confirmation of the discovered metabolites in saliva at the primary carcinoma site by DESI-MSI.

Figure S9. The MSE changes with the lambda during the 11th round of Lasso model training.

Figure S10. Pipeline of nearly real-time molecular diagnosis of OSCC by CPSI-MS/ML using the MATLAB/Simulink system. (A) The pipeline for data format conversion from .raw to .cdf followed by importing into MATLAB for automatic data processing including metabolic feature extraction and prediction. (B) The Lasso regression model consisted of different function blocks in Simulink to stimulate the scan-by-scan molecular diagnosis at nearly real-time. (C) The simulated real-time diagnosis process at three different times.

Figure S11. The representative high-throughput MS collection from the validation batch. (A) Representative TIC graph for high throughput screening of 60 samples within 40 minutes; (B) The zoomed TIC focused on single case with the time window of 0.83-1.03 minutes; (C) The mass spectrum averaged from the scans with that time window.

Figure S12. Mass spectra of saliva collected after meal directly (A) and after mouth prerinsing (B).

Figure S13. Box plots of representative metabolites that had continuous change tendencies from HC to OSCC.

Figure S14. Schematic of cross-validation procedure. The yellow 5% represents the test fold in each round of cross-validation, while the rest in gray corresponds to the training fold. The selected model from round 11 has been indicated by the red box.

Sample Batch	Characteristics	OSCC	PML	HC
Discovery	Race	Chinese	Chinese	Chinese
	Numbers	65	64	64
	Age (Range)	35-65	35-65	30-60
	Gender (M/F)	35/30	34/30	34/30
	Prior-therapy	N	${\sf N}$	----
	Stages	Stage:	Subtype	
		l: 15	OLP: 40	
		II: 21	OLK: 24	
		III: 12		
		IV: 17		
	Tumor sites	Tongue (21), cheek		
		(12), jaw (3),		
		mouth floor (6),		
		gums (9), palate		
		(4), lips (2),		
		oropharynx (7)		
Validation	Race	Chinese	Chinese	Chinese
	Numbers	60	60	60
	Age (Range)	35-65	$35 - 65$	30-60
	Gender (M/F)	30/30	30/30	30/30
	Prior-therapy	${\sf N}$	${\sf N}$	
	Stages:	Stage	Subtype:	----
		l: 14	OLP: 40	
		II: 19	OLK: 20	
		III: 11		
		IV: 16		
	Tumor sites	Tongue (19), jaw		
		(3), cheek (12),		
		mouth floor (6),		
		gums (9), palate		
		(4) , lip (1) ,		
		oropharynx (6),		

Table S1. Summary of information on OSCC patients, PML patients, and HC volunteers.

Table S2. Tentative assignment of metabolite ions.

Table S2 (Continued)

Table S2 (Continued)

Bold annotations represent those metabolite that identified with CID-MS/MS experiment.

Table S3. Summary of significantly changed metabolites between healthy and premalignant lesions.

***FC represent fold change of PML versus HC, only metabolites with FC values larger than 2.0 or smaller than 0.5 were listed in the table.**

Table S4. Summary of significantly changed metabolites between premalignant lesions and oral squamous cell carcinoma.

Table S4. (continued)

***FC represents fold change of OSCC versus PML, only metabolites with FC values larger than 2.0 or smaller than 0.5 were listed in the table.**

Metabolic Pathway	Hits/Total	$-LOG_{10}(p)$	FDR	Impact	Related Metabolites
Aminoacyl-tRNA	6/48	2.95597	0.092966	0	histidine; phenylalanine; arginine;
biosynthesis					aspartate; lysine; proline
lysine degradation	3/25	2.48745	0.13671	0.14554	cadaverine, piperidine, N-acetyl
					cadaverine
histidine metabolism	3/16	2.15080	0.19786	0.22131	histidine, N-methyl-
					histidine, aspartate
glycerophospholipid	5/36	1.90847	0.21485	0.04684	choline, phosphorylcholine,
metabolism					glycerophosphocholine, phosphoryl
					ethanolamine, ethanolamine
arginine and proline	4/38	1.82664	0.21485	0.2678	arginine, proline, putrescine,
metabolism					N-acetyl putrescine
sphingolipid metabolism	3/21	1.81398	0.21485	0.21298	sphinganine, sphingosine,
					phosphoryl ethanolamine
arginine biosynthesis	2/14	1.31343	0.51491	0.07614	arginine, aspartate

Table S5. Summary of altered metabolic pathways during progression from normal status to premalignant lesion.

Table S6. Summary of altered metabolic pathways during progression from healthy control to oral squamous cell carcinoma.

metabolite	adduct ion	cmz	weight
unknown		50.1464	0.0009092
unknown	---	52.2135	0.0111833
unknown		54.5165	0.0218527
unknown	---	55.2138	0.0104898
unknown	---	57.487	0.0321527
unknown		58.6449	-0.0026
unknown		59.6839	0.0211827
unknown	---	65.5846	0.0380753
unknown		74.9782	-0.039842
Cadaverine	$[M+H]^+$	103.1227	0.0206961
unknown		110.0717	-0.0051
Hypoxanthine	$[M+H]^+$	137.0458	0.0008847
proline	$[M+Na]^+$	138.0525	-0.011193
Taurine	$[M+Na]^+$	148.0035	-0.015395
Proline	$[M+K]^+$	154.0265	-0.027758
creatine	$[M+Na]^+$	154.0587	-0.02682
Glutamine	$[M+Na]$ ⁺	169.0584	-0.012903
Creatine	$[M+K]^+$	170.0323	-0.010836
N6, N6, N6-Trimethyl-L-lysine	$[M+H2O-H]^+$	171.149	0.0384406
unknown	---	178.133	0.0297669
unknown		181.5096	0.0164721
unknown	---	182.5849	0.0424328
Cytosine	$[M+2K-H]^+$	187.9574	-0.0558
N-(gamma-Glutamyl) ethanolamine	$[M+H]^+$	191.1026	0.0011292
dimethylarginine	$[M+H]^+$	203.1498	-0.005698
Tyrosine	$[M+Na]^+$	204.0627	0.1502359
unknown		212.0396	-0.026289
Vanillylmandelic acid	$[M+Na]^+$	221.0417	-0.043441
Hydroxydodecanoic acid	$[M+Na]+$	239.1599	0.0036741
Phenylalanine	$[M+2K-H]^+$	241.9998	0.0310015
Dihydrodipicolinate	$[M+2K-H]^+$	245.9537	-0.017957

Table S7. Weight coefficients of the metabolite ions in Lasso regression model.

Table S7 (Continued)

Accuracy (%)					
Round	Training set	Testing set	Lambda	DF	
$1\,$	95.08	90.00	0.025393	49	
2	93.99	100.00	0.024885	55	
3	93.48	100.00	0.027336	45	
4	93.99	90.00	0.027282	50	
5	95.08	70.00	0.025166	54	
6	94.02	66.67	0.025066	47	
$\overline{7}$	94.02	88.89	0.027334	50	
8	94.02	100.00	0.02733	49	
9	94.54	100.00	0.024869	52	
10	94.57	100.00	0.020676	56	
11	95.63	90.00	0.020644	62	
12	93.37	75.00	0.030385	37	
13	94.02	88.89	0.024979	55	
14	91.30	88.89	0.032921	42	
15	92.39	88.89	0.030012	45	
16	96.72	80.00	0.020864	66	
17	94.51	90.91	0.020725	60	
18	93.48	77.78	0.02778	48	
19	95.11	88.89	0.025127	48	
20	93.44	80.00	0.027485	45	

Table S8. The Lasso performance during the 20-fold cross validation.

	Training dataset (first batch of 193 cases)			
Target/Predict	HС	PML	OSCC	
HC.	62	З		
PML	$\left(\right)$	62	2	
OSCC	$\left(\right)$		60	
General accuracy	95.3%			

Table S9. Prediction performance of the developed Lasso regression model.

Training	PML vs HC	OSCC vs PML	OSCC vs HC
AUC (CI)	0.9966	0.9968	1.000
Sensitivity	100.0%	93.75%	100.0%
Specificity	98.46%	98.44%	98.46%

Table S10. Results of ROC analysis for the training and validation datasets

CI: 95% confidence interval

			Training Dataset		Validation Dataset	
Task	Model	Features*	Accuracy	MSE	Accuracy	MSE
Classification	ANN	626/626	96.4%	0.1430	90.0%	0.2333
Regression	Lasso	62/626	95.3%	0.1135	86.7%	0.1724
Regression	Quadratic	626/626	92.7%	0.1173	81.7%	0.1667
	SVM					
Classification	Cosine KNN	626/626	92.7%	0.1192	84.4%	0.2722
Regression	Ensemble	626/626	88.1%	0.1346	83.3%	0.1776
	Boosted)					
	Trees)					
Regression	Coarse DT	626/626	85.5%	0.1427	80.0%	0.2804
Classification	Kernal NB	626/626	79.3%	0.2383	55.6%	0.4944

Table S11. The models' performance comparison for the two batches of dataset.

*****The internal standard peak was excluded.