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Genome-Scale Analysis Identified *NID2*, *SPARC*, and *MFAP2* as Prognosis Markers of Overall Survival in Gastric Cancer

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Data Interpretation D
Manuscript Preparation E
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Background: Gastric cancer is the most common gastrointestinal tumor, and the rates of recurrence and metastasis are high. Research results on molecular biomarkers used for prognosis of gastric cancer remain inconclusive. This study aimed to explore the gene expression module of gastric cancer and to determine potential prognostic biomarkers.

Material/Methods: Three microarray datasets (GSE13911, GSE79973, and GSE29272) from Gene Expression Omnibus (GEO), including 206 pairs of gastric tumors and adjacent normal samples, were used for analysis of differentially expressed genes (DEGs). The 3 microarray datasets yielded 144 genes associated with the progression and prognosis of gastric cancer. After this, a risk score model was developed for result validation using an independent dataset from The Cancer Genome Atlas.

Results: The validation of the independent dataset showed significantly increased *NID2*, *SPARC*, and *MFAP2* expression in gastric tumor tissues, which were associated with poor outcomes in gastric cancer patients. Moreover, the high risk score obtained was associated with poor overall survival (HR: 1.787; 1.069-2.986; $P=0.027$). Subgroup analyses revealed that these significant prognostic values were detected in patients aged <65.0 years, tumors in the antrum/distal colon, grade 3 tumors, or TNM-M0 stages of cancer.

Conclusions: The findings of this study show that *NID2*, *SPARC*, and *MFAP2* are upregulated in gastric tumor tissues and are significantly associated with poor overall survival. Therefore, the predictive values of the risk score model employed for the prognosis of gastric cancer could be improved by using these 3 upregulated DEGs.

Keywords: **Biological Markers • Models, Genetic • Stomach Neoplasms**

Abbreviations: **DEGs – differentially expressed genes; GEO – Gene Expression Omnibus**

Full-text PDF: <https://www.medscimonit.com/abstract/index/idArt/929558>

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Background

Gastric cancer is the third leading cause of cancer-related deaths in the world, accounting for 8.2% of all cancer-related deaths [1,2]. Effective preventive and treatment strategies are required to improve the treatment and prognosis of gastric cancer, especially in Asian countries. Currently, the overall survival of gastric cancer has already been improved due to the diagnosis of the disease at an early stage and the timely application of adjuvant chemotherapy [3-5]. Although the advances in the multidisciplinary approaches and the combination treatment regimen, the prognosis of advanced gastric cancer remains dismal. Moreover, the heterogeneity of somatic or germline changes in patients are associated with the prognosis of gastric cancer.

Earlier studies have already identified the potential value of genetic and epigenetic alterations for gastric cancer prognosis. These alterations affect cycle regulation, cell adhesion, angiogenesis, and tumor carcinogenesis, having a significant prognostic role in the survival outcome in gastric cancer patients [6-9]. Moreover, investigations have already evaluated the gene expression profile of gastric cancer based on DNA microarray data, and explored the potential role of differentially expressed genes (DEGs) in the prognosis of gastric cancer [10-12]. However, the results of the above studies are limited due to their small sample sizes and the lack of validation datasets established in clinical practice. Hence, the use of the identified DEGs for prognosis of gastric cancer has been limited. Therefore, potential novel DEGs should be identified

whose role in the overall survival in gastric cancer patients should be assessed.

The potential role of genes in the progression and prognosis of gastric cancer could be revealed through microarray analysis [13,14]. Three microarray data (GSE13911, GSE79973, and GSE29272) were integrated and 144 DEGs were identified. After the validation of DEGs in The Cancer Genome Atlas (TCGA), we noted that *NID2*, *SPARC*, and *MFAP2* were more significantly upregulated in gastric tissues than in their adjacent normal tissues. Therefore, the high expression of *NID2*, *SPARC*, and *MFAP2* might affect the prognosis for GC, and the risk scores determined on the basis of *NID2*, *SPARC*, and *MFAP2* expression on OS in patients with GC after adjustment for potential confounders should be explored.

Material and Methods

Gastric Cancer Datasets

The Gene Expression Omnibus (GEO, <https://www.ncbi.nlm.nih.gov/geo/>) was applied to obtain the discovery and validation datasets. Three independent gastric cancer microarray datasets – GSE13911, GSE79973, and GSE29272 – were used to identify the DEGs, with 206 pairs of gastric tumors and adjacent normal samples. These datasets were generated on the basis of GPL570 platforms (Affymetrix Human Genome U113 Plus 2.0 Array) and GPL6947 platforms (Illumina HumanHT-12 V3.0 expression beadchip). GSE13911 and GSE79973 datasets

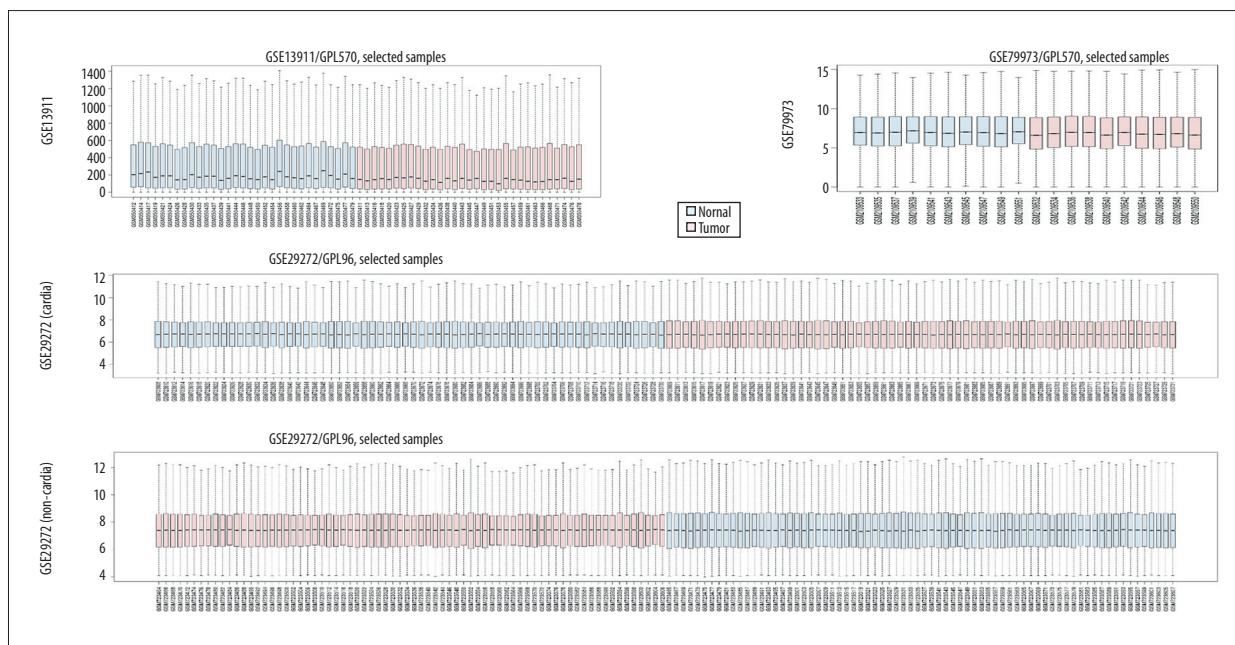


Figure 1. The details regarding the expression data from primary gastric tumors and adjacent normal samples in 4 subsets of 3 datasets.

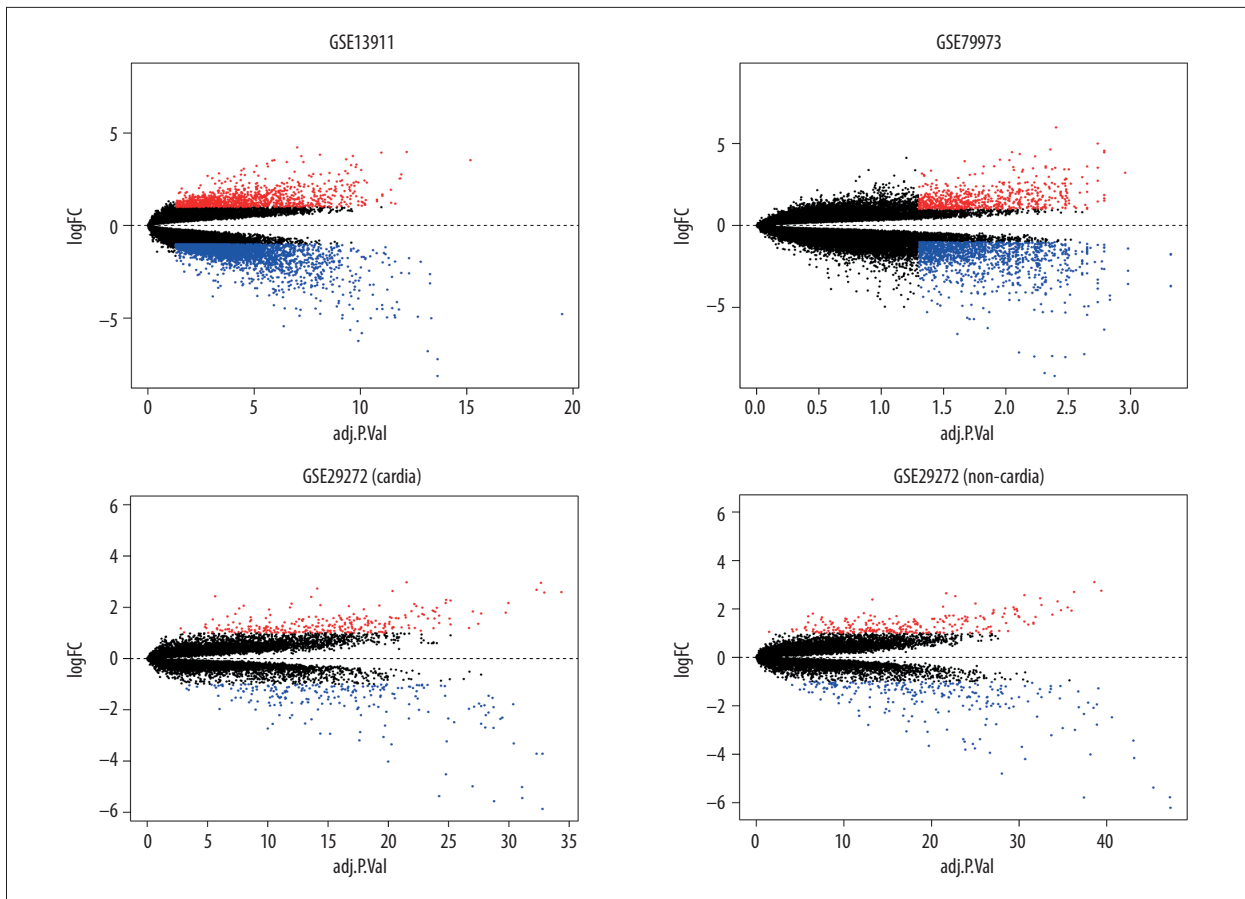


Figure 2. Identification of differentially expressed genes. Visualization of the identified differentially expressed genes was performed by volcano plots. Dots represent genes with color coding: red indicates upregulated, blue indicates downregulated, and black indicates genes that are not differentially expressed.

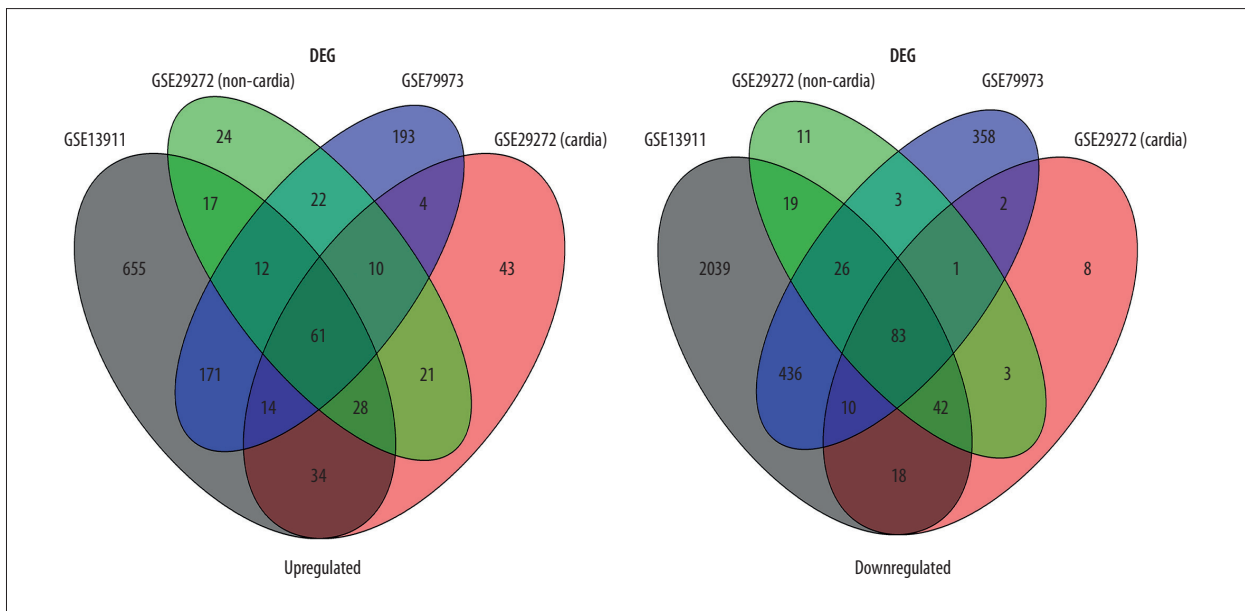


Figure 3. Venn diagram of the overlapping parts of the 4 subsets of 3 datasets of differentially expressed genes. Sixty-one genes were upregulated and 83 were downregulated.

Table 1. Common differentially expressed genes identified in gastric cancer.

Regulation	DEGs (gene symbol)		
Upregulated	APOC1	CTSB	NEK2
	APOE	CXCL8	NID2
	ASPM	ECT2	NT5DC2
	ASPN	FAP	OLFML2B
	BGN	FBN1	PMEPA1
	CAMK2N1	FCER1G	PRC1
	CDH11	FN1	RAB31
	CEMIP	GPNMB	RARRES1
	CEP55	HOXC6	S100A10
	COL10A1	IGF2BP3	SERPINH1
	COL11A1	IGFBP7	SFRP4
	COL1A1	INHBA	SPARC
	COL1A2	KPNA2	SPP1
	COL3A1	LEF1	SULF1
	COL4A1	LOC100129518///SOD2	THBS1
	COL4A2	LOC101928916///NNMT	THBS2
	COL5A1	LY6E	THY1
	COL5A2	MEST	TIMP1
	COL6A3	MFAP2	TOP2A
	CSE1L	CST1	VCAN
	MIR1292///SNORD110/// SNORD86///SNORD57///NOP56		
Downregulated	AADAC	COL2A1	KCNE2
	ADAM28	CPA2	KCNJ15
	ADGRG2	CYP2C18	KCNJ16
	ADH1C	DGKD	KIAA1324
	AKR1B10	EPB41L4B	KLF4
	AKR1C1	ESRRG	KRT20
	AKR7A3	ETNPPL	LIPF
	ALDH1A1	FA2H	LOC101930400///AKR1C2
	ALDH3A1	FBP2	LTF
	ALDH6A1	FCGBP	MAOA
	ATP4A	FMO5	METTL7A
	ATP4B	FOLR1	MT1E
	AZGP1	GC	MT1F

Table 1 continued. Common differentially expressed genes identified in gastric cancer.

Regulation	DEGs (gene symbol)		
Downregulated (continued)	AZGP1P1///AZGP1	GIF	MT1G
	CA2	GKN1	MT1H
	CA9	GPRC5C	MT1HL1
	CAPN9	GSTA1	MT1M
	CCKBR	HDC	MT1X
	CHGA	HPGD	MT2A
	CHIA	IGH	MUC5AC
	CKM	IGHA2///IGHA1///IGH	MYOC
	CKMT2	JCHAIN	MYRF
	NEDD4L	PIK3C2G	SLC16A7
	PBLD	PXMP2	SLC28A2
	PDGFD	RNASE1	SOSTDC1
	PGA4///PGA3///PGA5	S100P	SULT1C2
	PGC	UGT2B15	TMPRSS2
	XK	XYLT2	

composed 62 and 10 pairs of matched primary gastric tumors and their adjacent normal tissues, respectively. The GSE29272 dataset contained 62 pairs of cardia and 72 pairs of non-cardia gastric cancer. Data related to gastric cancer gene expression and in clinical practice were obtained from The Cancer Genome Atlas-Stomach Adenocarcinoma (TCGA-STAD). A total of 761 samples were identified, and 333 cases were selected in the survival analysis after removing the normal sample data and the data from patients with insufficient follow-up.

Data Preprocessing

The raw probe-level data in this study were downloaded in CEL files, and the robust multi-array average algorithm RMA from the Affy package of R software was employed for processing the raw probe-level data [15]. The background correction, quantile normalization, and summarizing probe set values into 1 expression measure were processed for analysis of the data of gene expression. The annotations for the probe arrays were obtained from GEO, and the mean of the probe sets values was considered as a value of the expression when multiple probe sets were mapped to the same gene [16]. In our study, the log FC in datasets met the criteria for normal distribution.

Statistical Analysis

The identified DEGs were evaluated using the LIMMA package, with bayesian adjusted t-statistics from the linear models for microarray data [17]. Genes with $|\log_2$ fold change (FC)| > 1 and $P < 0.05$ were regarded as DEGs between tumors and normal tissues. We constructed volcano plots and Venn diagrams using ggplot2, and Venn diagram packages of R software were used to visualize the identified DEGs.

The GO and KEGG pathway analyses of functional enrichment analysis for 144 common DEGs was conducted by using the online software Database for Annotation, Visualization, and Integrated Discovery (DAVID, <https://david.ncifcrf.gov/>). All P values are 2-sided, and $P < 0.05$ was considered to indicate statistically significant enrichment.

SPSS software (version 22.0, SPSS, Chicago, IL, USA) was used for statistical analysis. The risk score model consisted of gene expression, which could be validated in TCGA database. Next, the risk score model was constructed in TCGA-STAD, and the risk score of each individual patient was calculated. Moreover, the risk score was categorized into high and low, and the cutoff value was set to be the median of the risk score. The baseline characteristics between groups were compared using Kruskal-Wallis and chi-square tests based on the type of data. The propensity score analysis was used to adjust for imbalance in

Table 2. GO analysis of the 144 differentially expressed genes.

Category	Term	Count	P value	Benjamini	FDR	Genes
GOTERM_BP_DIRECT	GO: 0030198 ~extracellular matrix organization	21	5.81E-17	1.15E-13	1.78E-13	COL4A2, COL4A1, OLFML2B, COL3A1, FBN1, COL2A1, SPARC, NID2, COL5A2, COL5A1, BGN, COL6A3, COL1A2, MFAP2, VCAN, COL1A1, THBS1, COL11A1, SPP1, FN1, COL10A1
GOTERM_MF_DIRECT	GO: 0005201 ~extracellular matrix structural constituent	13	9.89E-14	3.07E-11	1.33E-10	COL4A2, BGN, COL4A1, COL3A1, FBN1, COL1A2, COL2A1, VCAN, COL1A1, MUC5AC, COL5A2, COL11A1, COL5A1
GOTERM_CC_DIRECT	GO: 0005576 ~extracellular region	42	4.25E-13	7.69E-11	5.24E-10	GC, CHIA, IGFBP7, COL3A1, JCHAIN, APOC1, CXCL8, COL2A1, TIMP1, AZGP1, APOE, COL6A3, CPA2, LTF, PDGFD, THBS1, COL11A1, THBS2, SPP1, COL10A1, FN1, ADAM28, COL4A2, COL4A1, OLFML2B, FBN1, GIF, NID2, SPARC, COL5A2, COL5A1, INHBA, BGN, SFRP4, CEMIP, COL1A2, VCAN, MFAP2, COL1A1, CTSB, MUC5AC, LIPF
GOTERM_CC_DIRECT	GO: 0031012 ~extracellular matrix	20	5.14E-13	4.65E-11	6.33E-10	ASPN, COL4A2, COL4A1, IGFBP7, COL3A1, FBN1, COL2A1, NID2, COL5A2, COL5A1, BGN, APOE, COL6A3, COL1A2, VCAN, COL1A1, THBS1, THBS2, MYOC, FN1
GOTERM_CC_DIRECT	GO: 0005615 ~extracellular space	38	8.88E-13	5.36E-11	1.10E-09	GC, CHIA, PGC, IGFBP7, COL3A1, JCHAIN, CXCL8, COL2A1, SERPINH1, ALDH3A1, TIMP1, AZGP1, APOE, SOSTDC1, FAP, COL6A3, CPA2, LTF, PDGFD, THBS1, MYOC, SPP1, FN1, ATP4A, FBN1, GIF, CST1, SPARC, CHGA, SFRP4, SULF1, COL1A2, VCAN, COL1A1, CTSB, MUC5AC, CA2, GKN1
GOTERM_BP_DIRECT	GO: 0030574 ~collagen catabolic process	12	2.42E-12	1.26E-09	3.85E-09	COL4A2, COL4A1, COL3A1, COL6A3, COL1A2, COL2A1, COL1A1, CTSB, COL11A1, COL5A2, COL5A1, COL10A1
GOTERM_CC_DIRECT	GO: 0070062 ~extracellular exosome	51	3.44E-10	1.56E-08	4.24E-07	RARRES1, PGC, IGFBP7, KIAA1324, AZGP1, APOE, LTF, AKR7A3, PDGFD, AKR1C1, ALDH6A1, FBP2, METTL7A, THY1, BGN, AKR1B10, COL1A2, CTSB, CA2, GC, GPRC5C, JCHAIN, APOC1, SERPINH1, PBLD, TIMP1, ALDH1A1, CSE1L, FOLR1, COL6A3, SULT1C2, NEDD4L, THBS1, MYOC, SPP1, FN1, MEST, GSTA1, TMPRSS2, RNASE1, COL4A2, S100P, FBN1, S100A10, NID2, ADGRG2, COL5A1, MUC5AC, FCGBP, HPGD, CDH11
GOTERM_CC_DIRECT	GO: 0005581 ~collagen trimer	11	1.32E-09	4.79E-08	1.63E-06	COL3A1, COL6A3, COL1A2, COL2A1, COL1A1, COL11A1, SERPINH1, COL5A2, COL5A1, COL10A1, TIMP1
GOTERM_CC_DIRECT	GO: 0005788 ~endoplasmic reticulum lumen	14	1.55E-09	4.68E-08	1.91E-06	COL4A2, COL4A1, COL3A1, COL6A3, COL1A2, COL2A1, COL1A1, PDGFD, THBS1, SERPINH1, COL5A2, COL11A1, COL5A1, COL10A1

Table 2 continued. GO analysis of the 144 differentially expressed genes.

Category	Term	Count	P value	Benjamini	FDR	Genes
GOTERM_BP_DIRECT	GO: 0071294~cellular response to zinc ion	7	5.25E-09	1.82E-06	8.34E-06	MT1M, MT2A, MT1E, MT1H, MT1X, MT1G, MT1F
GOTERM_BP_DIRECT	GO: 0045926~negative regulation of growth	7	5.25E-09	1.82E-06	8.34E-06	MT1M, MT2A, MT1E, MT1H, MT1X, MT1G, MT1F
GOTERM_CC_DIRECT	GO: 0005578 ~proteinaceous extracellular matrix	15	1.01E-08	2.62E-07	1.25E-05	ASPN, OLFML2B, FBN1, SPARC, COL5A2, COL5A1, TIMP1, BGN, COL6A3, COL1A2, VCAN, COL11A1, MYOC, FN1, COL10A1
GOTERM_MF_DIRECT	GO: 0048407 ~platelet-derived growth factor binding	6	1.07E-08	1.66E-06	1.44E-05	COL4A1, COL3A1, COL1A2, COL2A1, COL1A1, COL5A1
GOTERM_BP_DIRECT	GO: 0030199~collagen fibril organization	8	1.97E-08	5.12E-06	3.13E-05	COL3A1, COL1A2, COL2A1, COL1A1, COL11A1, SERPINH1, COL5A2, COL5A1
GOTERM_MF_DIRECT	GO: 0050840 ~extracellular matrix binding	6	1.39E-06	1.44E-04	0.001872262	BGN, OLFML2B, SPARC, THBS1, COL11A1, SPP1
GOTERM_CC_DIRECT	GO: 0005604 ~basement membrane	8	1.76E-06	3.99E-05	0.002172174	COL4A1, FBN1, COL2A1, NID2, SPARC, THBS2, COL5A1, TIMP1
GOTERM_BP_DIRECT	GO: 0007155 ~cell adhesion	16	3.26E-06	6.77E-04	0.005182285	ATP4B, IGFBP7, NID2, COL5A1, THY1, AZGP1, FAP, COL6A3, VCAN, COL1A1, THBS1, GPNMB, THBS2, SPP1, FN1, CDH11
GOTERM_BP_DIRECT	GO: 0071276~cellular response to cadmium ion	5	8.02E-06	0.001386589	0.012731623	MT1E, MT1H, MT1X, MT1G, MT1F
GOTERM_BP_DIRECT	GO: 0007586~digestion	7	9.91E-06	0.001467951	0.015725541	CHIA, CCKBR, PGC, AKR1B10, CAPN9, GKN1, AKR1C1
GOTERM_BP_DIRECT	GO: 0001501~skeletal system development	9	1.26E-05	0.001632159	0.019983654	COL3A1, FBN1, COL1A2, COL2A1, VCAN, COL1A1, COL5A2, COL10A1, CDH11
GOTERM_MF_DIRECT	GO: 0005178 ~integrin binding	8	1.58E-05	0.001223983	0.021220906	FAP, COL3A1, FBN1, THBS1, GPNMB, COL5A1, FN1, THY1

the baseline characteristics to avoid undue influences of confounding factors, which was analyzed using the MatchIt propensity score of R software, and the standardized mean difference for matching variables was defined as <20% between the groups. Kaplan-Meier and log-rank tests were employed for survival analysis. Subgroup analyses were also performed according to age, race, anatomic tumor site, grade, TNM-T, TNM-N, TNM-M, and stage. $P < 0.05$ was considered to indicate statistical significance.

Results

Identification of DEGs Between Gastric Tumors and Adjacent Normal Samples

GSE13911, GSE79973, and GSE29272 were employed as the discovery datasets for the identified DEGs expressed in gastric

tumors and their adjacent normal tissues. These 3 datasets included 206 pairs of gastric tumors and their adjacent normal samples. The DEGs were explored to evaluate the association between gene expression alteration and gastric cancer progression. The details regarding the expression data from primary gastric tumors and adjacent normal samples are shown in **Figure 1**. A total number of 144 DEGs were detected for the intersecting part of the 3 sets, which were generally related to gastric samples and potentially associated with the progression and prognosis of gastric cancer (**Figures 2, 3**). Detailed information of the 144 DEGs established is presented in **Table 1**.

Functional Enrichment Analysis of DEGs

GO and KEGG pathway enrichment analyses were performed to investigate the biological roles of DEGs in gastric cancer progression, including cell cycle and cell adhesion. The enriched GO terms were mainly associated with the extracellular

Table 3. KEGG pathway enrichment analysis of the 144 differentially expressed genes.

Category	Term	Count	P value	FDR	Genes
KEGG_PATHWAY	hsa04512: ECM-receptor interaction	14	3.93E-12	4.53E-09	COL4A2, COL4A1, COL3A1, COL2A1, COL5A2, COL5A1, COL6A3, COL1A2, COL1A1, THBS1, COL11A1, THBS2, SPP1, FN1
KEGG_PATHWAY	hsa04974: Protein digestion and absorption	12	1.48E-09	1.70E-06	COL4A2, COL4A1, COL3A1, COL6A3, COL1A2, CPA2, COL2A1, COL1A1, COL11A1, COL5A2, COL5A1, COL10A1
KEGG_PATHWAY	hsa04510: Focal adhesion	15	2.34E-08	2.69E-05	COL4A2, COL4A1, COL3A1, COL2A1, COL5A2, COL5A1, COL6A3, COL1A2, PDGFD, COL1A1, THBS1, COL11A1, THBS2, SPP1, FN1
KEGG_PATHWAY	hsa05146: Amoebiasis	11	1.36E-07	1.57E-04	COL4A2, COL4A1, COL3A1, COL1A2, CXCL8, COL2A1, COL1A1, COL11A1, COL5A2, COL5A1, FN1
KEGG_PATHWAY	hsa04978: Mineral absorption	7	5.95E-06	0.006851	MT1M, MT2A, MT1E, MT1H, MT1X, MT1G, MT1F
KEGG_PATHWAY	hsa04151: PI3K-Akt signaling pathway	15	1.22E-05	0.014013	COL4A2, COL4A1, COL3A1, COL2A1, COL5A2, COL5A1, COL6A3, COL1A2, PDGFD, COL1A1, THBS1, COL11A1, THBS2, SPP1, FN1
KEGG_PATHWAY	hsa04971: Gastric acid secretion	7	1.13E-04	0.129558	KCNJ16, KCNJ15, CCKBR, ATP4A, ATP4B, KCNE2, CA2
KEGG_PATHWAY	hsa04611: Platelet activation	8	4.23E-04	0.486191	COL3A1, COL1A2, FCER1G, COL2A1, COL1A1, COL11A1, COL5A2, COL5A1
KEGG_PATHWAY	hsa00982: Drug metabolism – cytochrome P450	6	7.27E-04	0.833392	GSTA1, FMO5, MAOA, ADH1C, UGT2B15, ALDH3A1
KEGG_PATHWAY	hsa00980: Metabolism of xenobiotics by cytochrome P450	6	0.001069	1.223788	GSTA1, ADH1C, AKR7A3, UGT2B15, AKR1C1, ALDH3A1
KEGG_PATHWAY	hsa05204: Chemical carcinogenesis	5	0.010061	10.99085	GSTA1, CYP2C18, ADH1C, UGT2B15, ALDH3A1
KEGG_PATHWAY	hsa00340: Histidine metabolism	3	0.022373	22.93516	HDC, MAOA, ALDH3A1
KEGG_PATHWAY	hsa00830: Retinol metabolism	4	0.030117	29.67766	ALDH1A1, CYP2C18, ADH1C, UGT2B15
KEGG_PATHWAY	hsa04966: Collecting duct acid secretion	3	0.032861	31.93507	ATP4A, ATP4B, CA2

matrix of the cellular component, and the KEGG pathway analysis results showed that the most highly enriched pathway was ECM-receptor interaction. The results of the GO and KEGG pathway enrichment analyses are summarized and displayed in **Tables 2 and 3**.

Validation of DEGs in an Independent Database

TCGA-STAD included 333 GC patients, who were regarded as a validation cohort, which was assessed to verify the expression of DEGs. The results indicated that *NID2*, *SPARC*, and *MFAP2* were the 3 top-ranked upregulated genes for the risk

of GC. Further, we developed a risk score model described by the following formula: risk score= $0.005974532 \times \text{Exp}_{NID2} + 0.004623909 \times \text{Exp}_{SPARC} + 0.054586198 \times \text{Exp}_{MFAP2}$. The categories of high and low risk scores were based on the median values of the of risk scores.

Risk Score and Overall Survival for Patients with Gastric Cancer

The baseline characteristics of the high (n=166) and low (n=167) risk score groups are presented in **Table 4**. Significant differences were observed between groups in terms of race and

Table 4. Baseline characteristics of patients in high and low risk score groups.

	Pre-propensity score matching			Post-propensity score matching		
	Low	High	P	Low	High	P
Age, median (Q1, Q3)	67.00 (58.00,72.00)	67.00 (58.00,72.00)	0.960	67.00 (58.00,72.00)	68.00 (59.00,72.00)	0.617
Gender						
Female	55 (33.13)	62 (37.13)	0.445	49 (35.51)	50 (36.23)	0.900
Male	111 (66.87)	105 (62.87)		89 (64.49)	88 (63.77)	
Race						
White	96 (57.83)	114 (68.26)	0.031	89 (64.49)	92 (66.67)	0.932
Asian	38 (22.89)	33 (19.76)		34 (24.64)	27 (19.57)	
Others	32 (19.28)	20 (11.98)		15 (10.87)	19 (13.77)	
Anatomic tumor site						
Antrum/distal	61 (36.75)	63 (37.72)	0.394	54 (39.13)	51 (36.96)	0.955
Fundus/body	56 (33.73)	62 (37.13)		47 (34.06)	51 (36.96)	
Cardia/proximal	24 (14.46)	20 (11.98)		19 (13.77)	17 (12.32)	
Gastroesophageal junction	18 (10.84)	20 (11.98)		13 (9.42)	18 (13.04)	
Others	7 (4.22)	2 (1.20)		5 (3.62)	1 (0.72)	
Grade						
G1	4 (2.41)	4 (2.40)	0.930	4 (2.90)	4 (2.90)	0.917
G2	60 (36.14)	55 (32.93)		48 (34.78)	43 (31.16)	
G3	98 (59.04)	103 (61.68)		83 (60.14)	87 (63.04)	
Gx	4 (2.41)	5 (2.99)		3 (2.17)	4 (2.90)	
TNM-T						
T1-2	44 (26.51)	38 (22.75)	0.427	35 (25.36)	36 (26.09)	0.891
T3-4	122 (73.49)	129 (77.25)		103 (74.64)	102 (73.91)	
TNM-N						
N0	53 (31.93)	55 (32.93)	0.533	44 (31.88)	47 (34.06)	0.419
N1	38 (22.89)	46 (27.54)		33 (23.91)	40 (28.99)	
N2	41 (24.70)	31 (18.56)		35 (25.36)	24 (17.39)	
N3	34 (20.48)	35 (20.96)		26 (18.84)	27 (19.57)	
TNM-M						
M0	157 (94.58)	153 (91.62)	0.287	131 (94.93)	128 (92.75)	0.453
M1	9 (5.42)	14 (8.38)		7 (5.07)	10 (7.25)	
Stage						
I	29 (17.47)	15 (8.98)	0.029	22 (15.94)	15 (10.87)	0.073
II	42 (25.30)	62 (37.13)		38 (27.54)	55 (39.86)	
III	75 (45.18)	67 (40.12)		63 (45.65)	50 (36.23)	
IV	14 (8.43)	20 (11.98)		10 (7.25)	16 (11.59)	

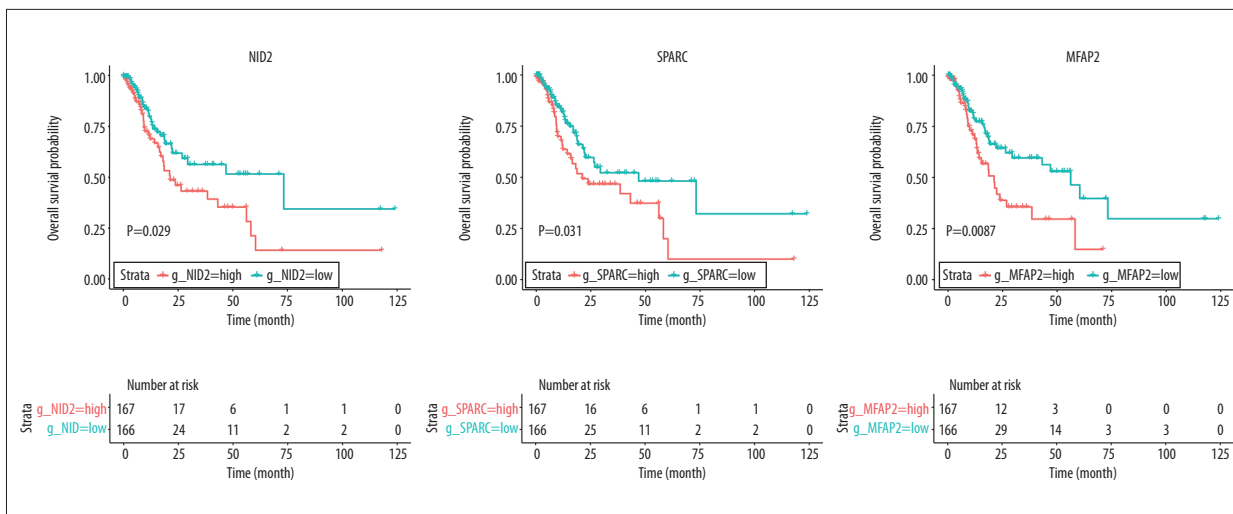


Figure 4. Overall survival according to the expression of NID2, SPARC, and MFAP2. Red line indicates high expression and blue line indicates low expression.

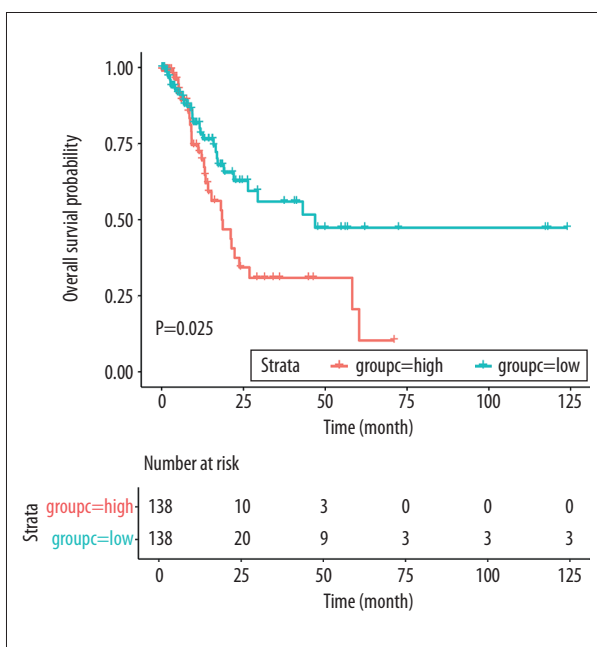


Figure 5. Overall survival according to the risk scores after propensity score analysis. Red line indicates high risk score and blue line indicates low risk score.

tumor stages, whereas no significant differences were established for age, sex, anatomic tumor site, tumor grade, TNM-T, TNM-N, and TNM-M. Overall, we noted that a high risk score was obviously associated with poor overall survival (HR: 2.041; 95% CI: 1.272-3.274; $P=0.003$; **Figure 4**). Significant associations were observed mainly in the following patients: <65.0 years, with a tumor in the antrum/distal colon, with a grade 3 tumor, irrespective of the TNM-T stage, TNM-N2-3, TNM-M0, and stage III and IV (**Table 2**). After propensity score analysis, the higher risk scores were associated with poorer overall

survival (HR: 1.787; 1.069-2.986; $P=0.027$; **Figure 5**). Subgroup analysis showed that high risk scores were associated with poor overall survival in patients age <65.0 years and if they had a tumor in the antrum/distal colon, grade 3 tumor, or TNM-M0 stages gastric cancer (**Table 5**).

Discussion

The gene expression modules at the genome-wide scale in gastric cancer were investigated in our study through integrating multiple gastric cancer transcriptome microarray datasets. Our findings provide information on alterations at the molecular level; we achieved higher robustness than that of data from a single dataset. We screened 144 DEGs in gastric tumors and adjacent normal samples and discovered that the expression levels of *NID2*, *SPARC*, and *MFAP2* were the 3 top-ranked upregulated genes. Next, a risk score model based on 3 DEGs was constructed ($\text{risk score} = 0.005974532 \times \text{Exp}_{\text{NID2}} + 0.004623909 \times \text{Exp}_{\text{SPARC}} + 0.054586198 \times \text{Exp}_{\text{MFAP2}}$), which was significantly associated with poor overall survival in patients with GC, based on data from TCGA database. Furthermore, using propensity score analysis, we observed these associations mainly in patients younger than 65.0 years, with a tumor in the antrum/distal colon, with a grade 3 tumor, or with TNM-M0 stages of GC.

The results of this study indicated that GC is involved in cell cycle, cell adhesion, and the extracellular matrix; these processes were found in patients with upregulated *NID2*, *SPARC*, and *MFAP2*. The cell adhesion dysfunction was significantly associated with gastric cancer metastasis, which could be considered to represent multiple activated signaling pathways in the malignancy [18]. Moreover, the common characteristics of

Table 5. Subgroup analyses for overall survival before and after propensity score analysis.

Factors	Group	Before propensity score		Propensity score analysis	
		HR and 95% CI	P-value	HR and 95%CI	P-value
Age (years)	<65.0	2.949 (1.283-6.774)	0.011	2.840 (1.161-6.945)	0.022
	>65.0	1.581 (0.890-2.808)	0.118	1.363 (0.725-2.562)	0.337
Race	White	1.700 (0.907-3.186)	0.098	1.530 (0.781-2.997)	0.215
	Asian	8.072 (0.823-79.156)	0.073	6.308 (0.571-69.650)	0.133
Anatomic tumor site	Antrum/distal	3.278 (1.553-6.922)	0.002	3.018 (1.353-6.732)	0.007
	Fundus/body	1.904 (0.805-4.504)	0.143	1.392 (0.563-3.438)	0.474
	Position-others	1.082 (0.423-2.770)	0.869	1.133 (0.408-3.150)	0.810
Grade	1-2	1.933 (0.904-4.131)	0.089	1.320 (0.592-2.942)	0.497
	3	2.376 (1.275-4.428)	0.006	2.576 (1.267-5.238)	0.009
TNM-T	T1-2	3.838 (1.130-13.038)	0.031	3.590 (0.937-13.760)	0.062
	T3-4	1.856 (1.103-3.124)	0.020	1.639 (0.926-2.901)	0.090
TNM-N	N0-1	1.873 (0.923-3.802)	0.082	1.746 (0.840-3.627)	0.135
	N2-3	2.127 (1.114-4.064)	0.022	1.695 (0.812-3.539)	0.160
TNM-M	M0	2.132 (1.274-3.567)	0.004	1.843 (1.055-3.217)	0.032
	M1	1.103 (0.333-3.651)	0.872	1.149 (0.305-4.329)	0.837
Stage	I and II	2.305 (0.855-6.215)	0.099	2.291 (0.782-6.712)	0.131
	III and IV	2.095 (1.191-3.685)	0.010	1.652 (0.893-3.055)	0.110

CI – confidence interval; HR – hazard ratio; M – metastasis; N – node; T – tumor.

gastric cancer were the dense stroma with enormous quantities of extracellular matrix in the surrounding area [19,20]. The gene annotation analysis results support our findings on the enriched cellular components of extracellular matrix and ECM-receptor interaction pathway.

We noted the expression of *NID2*, *SPARC*, and *MFAP2* in gastric tumors was upregulated compared with adjacent normal tissue samples. The role of abnormal *NID2* methylation in cancer prognosis at various sites has already been highlighted in previous research [21-25]. *NID2*, which is a member of the nidogen protein family, has been reported to maintain the stability and integrity of the basement membrane. Moreover, the involvement of *SPARC* in the prognosis of gastric cancer has also been confirmed in many studies [26-28]. The study conducted by Liao et al identified 4 microarray datasets and found *SPARC* is significantly upregulated in gastric tissues, which was associated with poor prognosis [26]. Evidence has shown that cell adhesion, proliferation, migration, and tissue remodeling are regulated by *SPARC* during cell development and the extracellular matrix turnover processes [29,30]. Recently, *MFAP2* was found to modulate tropoelastin deposition into microfibrils, which participates in the formation of elastic fibers [31]. Moreover, it was considered as the co-expressed gene of the

NF-κB/Snail/YY1/RKIP circuitry, which was upregulated in tumor tissues; the extent of this upregulation was specific evidence of lymph node metastasis [32,33]. In the present study, we constructed a risk score model for predicting overall survival of gastric cancer patients, which showed that a high risk score was associated with poor overall survival. Moreover, stratified analyses of patients' characteristics also confirmed our findings.

Several limitations to this study should be acknowledged: (1) The interpretation of the results should be cautious due to the collection of data from different platforms; (2) Bioinformatics analysis was applied, whose findings should be verified in further research to clarify the mechanisms of the association between these genes and poor GC survival; (3) The range of the analyses was limited due to variations in the characteristics of the patients; and (4) The role of the expression of the studied 3 genes associated with other survival outcomes in patients with GC should be further explored, including the determination of progression-free survival.

Conclusions

In conclusion, the findings of this study suggest the upregulation of *NID2*, *SPARC*, and *MFAP2* is strongly associated with overall survival in patients with gastric cancer. Moreover, the risk score of the overall survival of gastric cancer patients is affected by age, the anatomic tumor site, tumor grade, and TNM-M. Further research should be conducted in laboratory settings to explore the underlying molecular mechanisms and to translate these research findings into the development of novel targeted-treatment strategies.

References:

1. Ferlay J, Soerjomataram I, Ervik M, et al. GLOBOCAN 2012 v1.0, Cancer Incidence and Mortality Worldwide: IARC CancerBase No. 11 Lyon, France: International Agency for Research on Cancer; <http://globocan.iarc.fr>, accessed on 06/018/2019
2. Bray F, Ferlay J, Soerjomataram I, et al. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *Cancer J Clin*. 2018;68(6):394-424
3. Information Committee of Korean Gastric Cancer Association. Korean Gastric Cancer Association Nationwide Survey on Gastric Cancer in 2014. *J Gastric Cancer*. 2016;16(3):131-40
4. Bang YJ, Kim YW, Yang HK, et al. Adjuvant capecitabine and oxaliplatin for gastric cancer after D2 gastrectomy (CLASSIC): A phase 3 open-label, randomised controlled trial. *Lancet*. 2012;379(9813):315-21
5. Sasako M, Sakuramoto S, Katai H, et al. Five-year outcomes of a randomized phase III trial comparing adjuvant chemotherapy with S-1 versus surgery alone in stage II or III gastric cancer. *J Clin Oncol*. 2011;29(33):4387-93
6. Akama Y, Yasui W, Yokozaki H, et al. Frequent amplification of the cyclin E gene in human gastric carcinomas. *Jpn J Cancer Res*. 1995;86(7):617-21
7. Graziano F, Mandolesi A, Ruzzo A, et al. Predictive and prognostic role of E-cadherin protein expression in patients with advanced gastric carcinoma treated with palliative chemotherapy. *Tumour Biol*. 2004;25(3):106-10
8. Tanigawa N, Amaya H, Matsumura M, et al. Correlation between expression of vascular endothelial growth factor and tumor vascularity, and patient outcome in human gastric carcinoma. *J Clin Oncol*. 1997;15(2):826-32
9. Sanz-Ortega J, Steinberg SM, Moro E, et al. Comparative study of tumor angiogenesis and immunohistochemistry for p53, c-ErbB2, c-myc and EGFR as prognostic factors in gastric cancer. *Histol Histopathol*. 2000;15(2):455-62
10. Cho JY, Lim JY, Cheong JH, et al. Gene expression signature-based prognostic risk score in gastric cancer. *Clin Cancer Res*. 2011;17(7):1850-57
11. Chen CN, Lin JJ, Chen JJ, et al. Gene expression profile predicts patient survival of gastric cancer after surgical resection. *J Clin Oncol*. 2005;23(29):7286-95
12. Wang X, Liu Y, Niu Z, et al. Prognostic value of a 25-gene assay in patients with gastric cancer after curative resection. *Sci Rep*. 2017;7(1):7515
13. Chang W, Ma L, Lin L, et al. Identification of novel hub genes associated with liver metastasis of gastric cancer. *Int J Cancer*. 2009;125(12):2844-53
14. Zhu T, Gao YF, Chen YX, et al. Genome-scale analysis identifies GJB2 and ERO1LB as prognosis markers in patients with pancreatic cancer. *Oncotarget*. 2017;8(13):21281-89
15. Irizarry RA, Hobbs B, Collin F, et al. Exploration, normalization, and summaries of high density oligonucleotide array probe level data. *Biostatistics*. 2003;4(2):249-64
16. Li W, Li K, Zhao L, et al. Bioinformatics analysis reveals disturbance mechanism of MAPK signaling pathway and cell cycle in Glioblastoma multiforme. *Gene*. 2014;547(2):346-50

Conflict of Interest

None.

17. Diboun I, Wernisch L, Orengo CA, et al. Microarray analysis after RNA amplification can detect pronounced differences in gene expression using limma. *BMC Genomics*. 2006;7:252
18. Liu JP, Liu D, Gu JF, et al. Shikonin inhibits the cell viability, adhesion, invasion and migration of the human gastric cancer cell line MGC-803 via the Toll-like receptor 2/nuclear factor-kappa B pathway. *J Pharm Pharmacol*. 2015;67(8):1143-55
19. Gan L, Meng J, Xu M, et al. Extracellular matrix protein 1 promotes cell metastasis and glucose metabolism by inducing integrin beta4/FAK/SOX2/HIF-1alpha signaling pathway in gastric cancer. *Oncogene*. 2018;37(6):744-55
20. Wu Q, Li X, Yang H, et al. Extracellular matrix protein 1 is correlated to carcinogenesis and lymphatic metastasis of human gastric cancer. *World J Surg Oncol*. 2014;12:132
21. Wang J, Zhao Y, Xu H, et al. Silencing NID2 by DNA hypermethylation promotes lung cancer. *Pathol Oncol Res*. 2020;26(2):801-11
22. Wu Q, Zhang B, Wang Z, et al. Integrated bioinformatics analysis reveals novel key biomarkers and potential candidate small molecule drugs in gastric cancer. *Pathol Res Pract*. 2019;215(5):1038-48
23. van der Heijden AG, Mengual L, Ingelmo-Torres M, et al. Urine cell-based DNA methylation classifier for monitoring bladder cancer. *Clin Epigenetics*. 2018;10:71
24. Chai AWY, Cheung AKL, Dai W, et al. Elevated levels of serum nidogen-2 in esophageal squamous cell carcinoma. *Cancer Biomark*. 2018;21(3):583-90
25. Torky HA, Sherif A, Abo-Louz A, et al. Evaluation of serum Nidogen-2 as a screening and diagnostic tool for ovarian cancer. *Gynecol Obstet Invest*. 2018;83(5):461-65
26. Liao P, Li W, Liu R, et al. Genome-scale analysis identifies SERPINE1 and SPARC as diagnostic and prognostic biomarkers in gastric cancer. *Oncotargets Ther*. 2018;11:6969-80
27. Li Z, Li AD, Xu L, et al. SPARC expression in gastric cancer predicts poor prognosis: Results from a clinical cohort, pooled analysis and GSEA assay. *Oncotarget*. 2016;7(43):70211-22
28. Wang Z, Hao B, Yang Y, et al. Prognostic role of SPARC expression in gastric cancer: A meta-analysis. *Arch Med Sci*. 2014;10(5):863-69
29. Funk SE, Sage EH. The Ca2(+)-binding glycoprotein SPARC modulates cell cycle progression in bovine aortic endothelial cells. *Proc Natl Acad Sci USA*. 1991;88(7):2648-52
30. Lane TF, Sage EH. The biology of SPARC, a protein that modulates cell-matrix interactions. *FASEB J*. 1994;8(2):163-73
31. Mecham RP, Gibson MA. The microfibril-associated glycoproteins (MAGPs) and the microfibrillar niche. *Matrix Biol*. 2015;47:13-33
32. Zaravinos A, Kanellou P, Lambrou GI, et al. Gene set enrichment analysis of the NF-kappaB/Snail/YY1/RKIP circuitry in multiple myeloma. *Tumour Biol*. 2014;35(5):4987-5005
33. Silveira NJ, Varuzza L, Machado-Lima A, et al. Searching for molecular markers in head and neck squamous cell carcinomas (HNSCC) by statistical and bioinformatic analysis of larynx-derived SAGE libraries. *BMC Med Genomics*. 2008;1:56