Intelligence artificielle et pathologie cervicale

Dr Arthur Foulon

Gynazur 2022

23/06/2022

UNIVERSITÉ de Picardie Jules Verne

SFCPCV

CHU AMIENS PICARDIE

DONNER UN SENS À L'INTELLIGENCE ARTIFICIELLE

POUR UNE STRATÉGIE
NATIONALE ET EUROPÉENNE

CÉDRIC VILLANI
Mathématicien et député de l'Essonne

Définir l'intelligence artificielle n'est pas chose facile. Depuis ses origines comme domaine de recherche spécifique, au milieu du XX^{e} siècle, elle a toujours constitué une frontière, incessamment repoussée. L'intelligence artificielle désigne en effet moins un champ de recherches bien défini qu'un programme, fondé autour d'un objectif ambitieux : comprendre comment fonctionne la cognition humaine et la reproduire ; créer des processus cognitifs comparables à ceux de l'être humain.

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POUR UNE STRATÉGIE NATIONALE ET EUROPÉENNE

CÉDRIC VILLANI

Mathématicien et député de l'Essonne

L'IA au service de la médecine

- un diagnostic et une stratégie thérapeutique plus adaptés
- mieux détecter les symptômes
- faire un suivi prédictif du déploiement d'une maladie
- exploiter les résultats d'analyse (imagerie médicale...)
- de formuler des propositions thérapeutiques plus personnalisées
- …

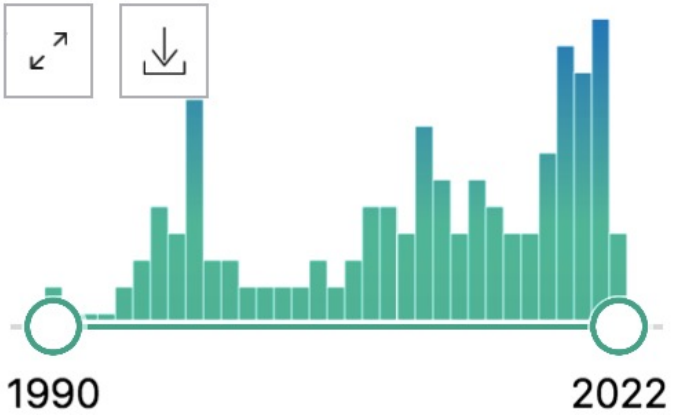
Pubmed

77 results

RESULTS BY YEAR

103 results

RESULTS BY YEAR



Test HPV-HR / Cytologie

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2019

Machine Learning Interpretation of Extended Human Papillomavirus Genotyping by Onclarity in an Asian Cervical Cancer Screening Population

Oscar G. W. Wong,[a] Idy F. Y. Ng,[a] Obe K. L. Tsun,[a] Herbert H. Pang,[b] Philip P. C. Ip,[a] Annie N. Y. Cheung[a]

605 tests HPV

TABLE 6 Rules identified by association rule mining

Rule	Support	Confidence	Rule power factor	Lift	Conviction	Count
1. {HPV16,HPV33/58} → {CIN2/3 or above}	0.017	0.909	0.015	3.374	8.036	10
2. {HPV16} → {CIN2/3 or above}	0.122	0.685	0.084	2.543	2.321	74
3. {HPV33/58,HPV35/39/68} → {CIN2/3 or above}	0.010	0.667	0.007	2.474	2.192	6
4. {HPV33/58,HPV52} → {CIN2/3 or above}	0.018	0.611	0.011	2.268	1.879	11
5. {HPV35/39/68,HPV52} → {CIN2/3 or above}	0.010	0.600	0.006	2.227	1.826	6
6. {HPV31} → {CIN2/3 or above}	0.015	0.563	0.008	2.088	1.670	9
7. {HPV16,HPV52} → {CIN2/3 or above}	0.012	0.538	0.006	1.999	1.583	7
8. {HPV33/58} → {CIN2/3 or above}	0.078	0.461	0.036	1.710	1.355	47
9. {HPV35/39/68} → {CIN2/3 or above}	0.036	0.344	0.013	1.276	1.113	22
10. {HPV18} → {CIN2/3 or above}	0.018	0.314	0.006	1.167	1.065	11
11. {HPV52} → {CIN2/3 or above}	0.050	0.291	0.014	1.081	1.031	30
12. {HPV51} → {CIN2/3 or above}	0.012	0.219	0.003	0.812	0.935	7
13. {HPV56/59/66} → {CIN2/3 or above}	0.020	0.169	0.003	0.627	0.879	12

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TABLE 7 Performance of the classifiers using Onclarity extended genotyping results to predict the outcome of the cases in the test set

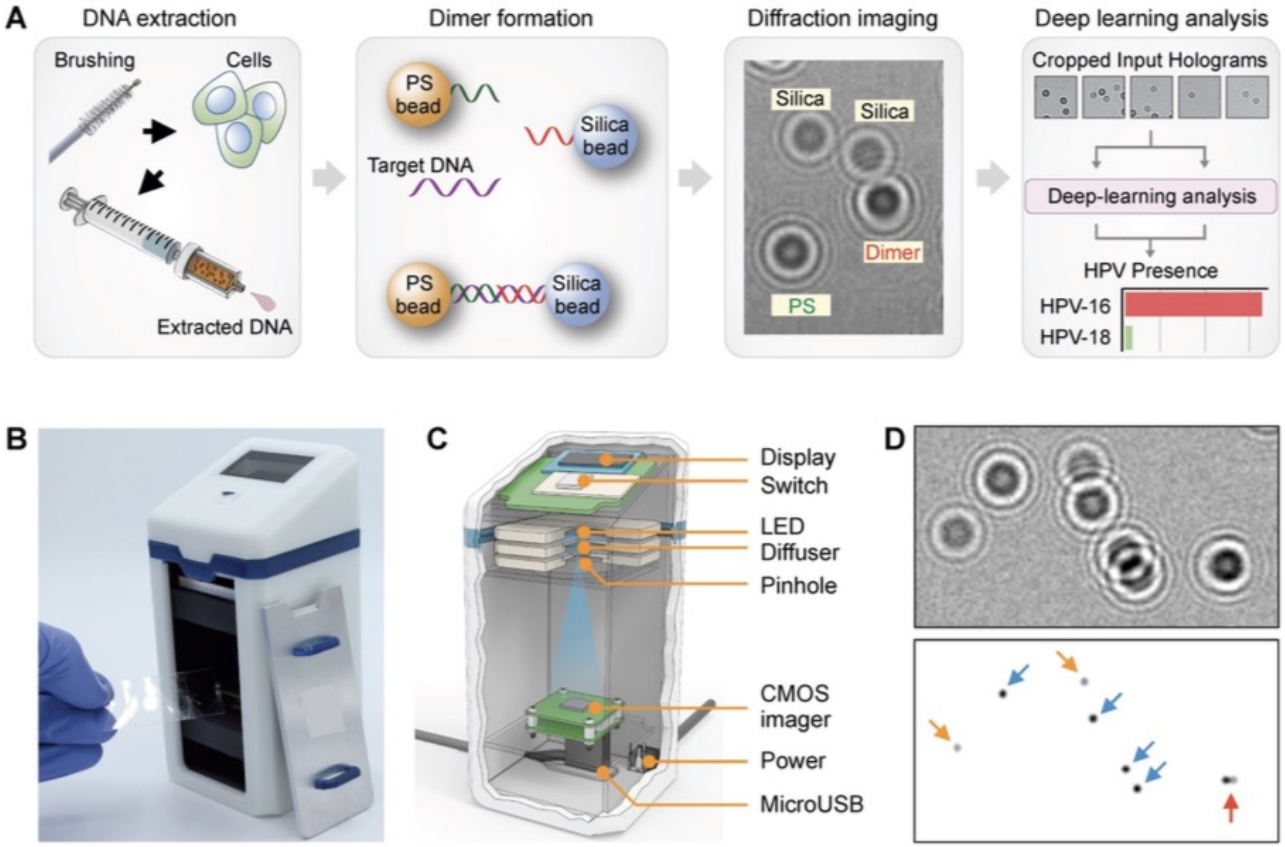
	Test result[a] [% (95% CI)]			
Classifier	**Sensitivity**	**Specificity**	**PPV**	**NPV**
hrHPV	96.88 (83.78–99.91)	51.14 (40.25–61.95)	41.89 (30.51–53.94)	97.83 (88.47–99.94)
hrHPV (HPV16 + HPV18)	62.50 (43.69–78.90)	89.77 (81.47–95.22)	68.97 (49.17–84.72)	86.81 (78.10–93.00)
Decision tree[b]	50.00 (31.89–68.11)	94.32 (87.24–98.13)	76.19 (52.83–91.78)	83.84 (75.09–90.47)
Random forest	53.13 (34.74–70.91)	90.91 (82.87–95.99)	68.00 (46.50–85.05)	84.21 (75.30–90.88)
SVM[c]-linear	56.25 (37.66–73.64)	90.91 (82.87–95.99)	69.23 (48.21–85.67)	85.11 (76.28–91.61)
SVM[c]-nonlinear	53.13 (34.74–70.91)	90.91 (82.87–95.99)	68.00 (46.50–85.05)	84.21 (75.30–90.88)

Research Paper

Theranostics

Point-of-care cervical cancer screening using deep learning-based microholography

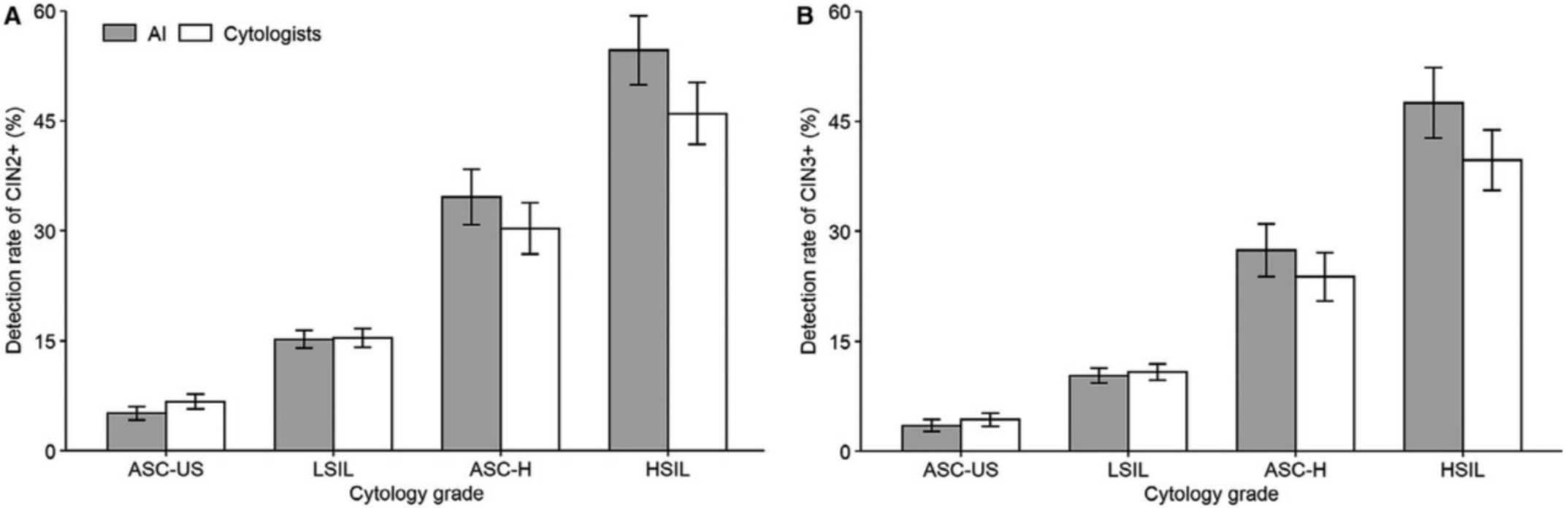
16000 échantillons



Pathania et al., 2019

Cancer Medicine
Open Access

The artificial intelligence-assisted cytology diagnostic system in large-scale cervical cancer screening: A population-based cohort study of 0.7 million women

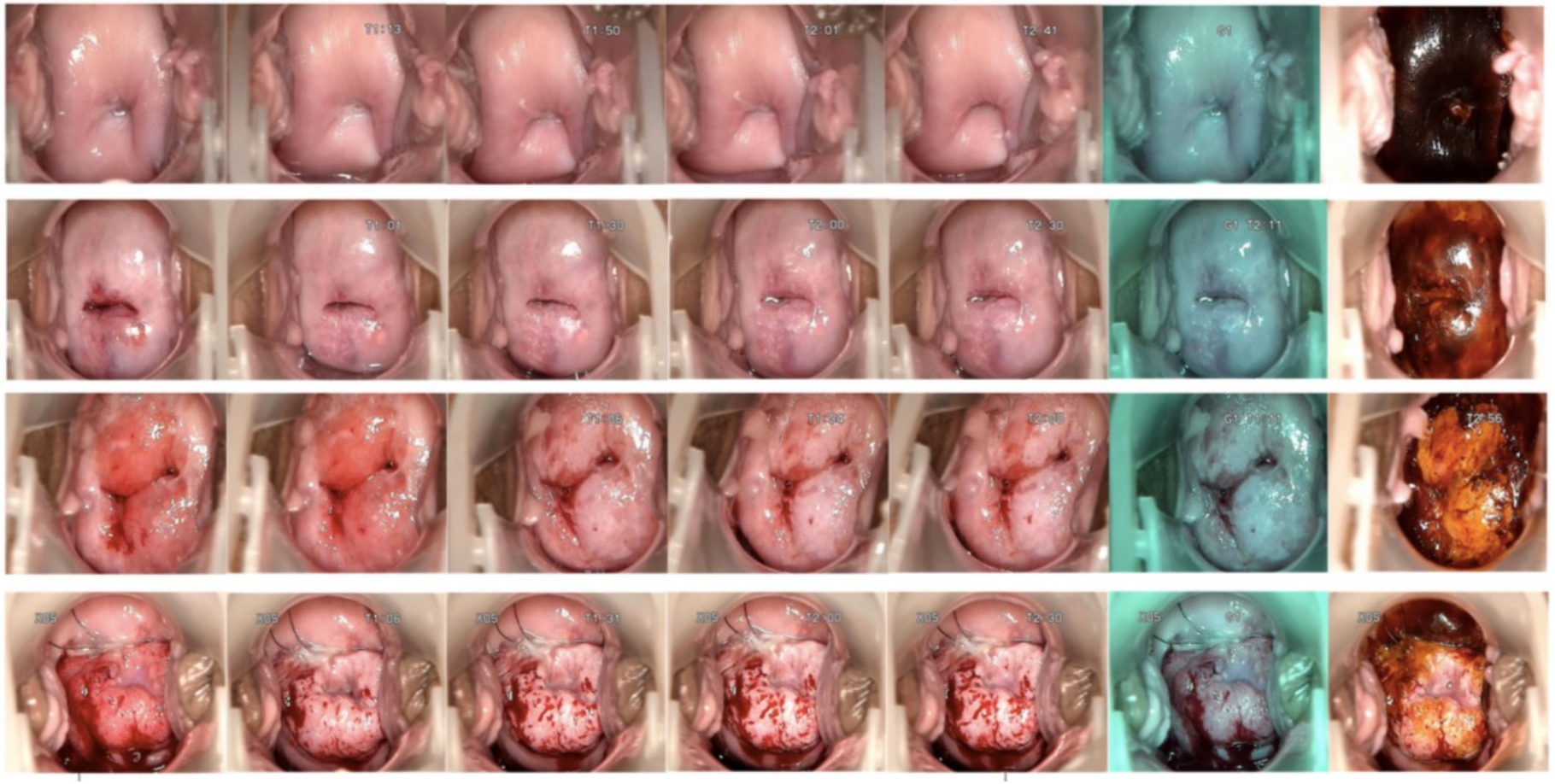


Bao et al., 2020

Colposcopie

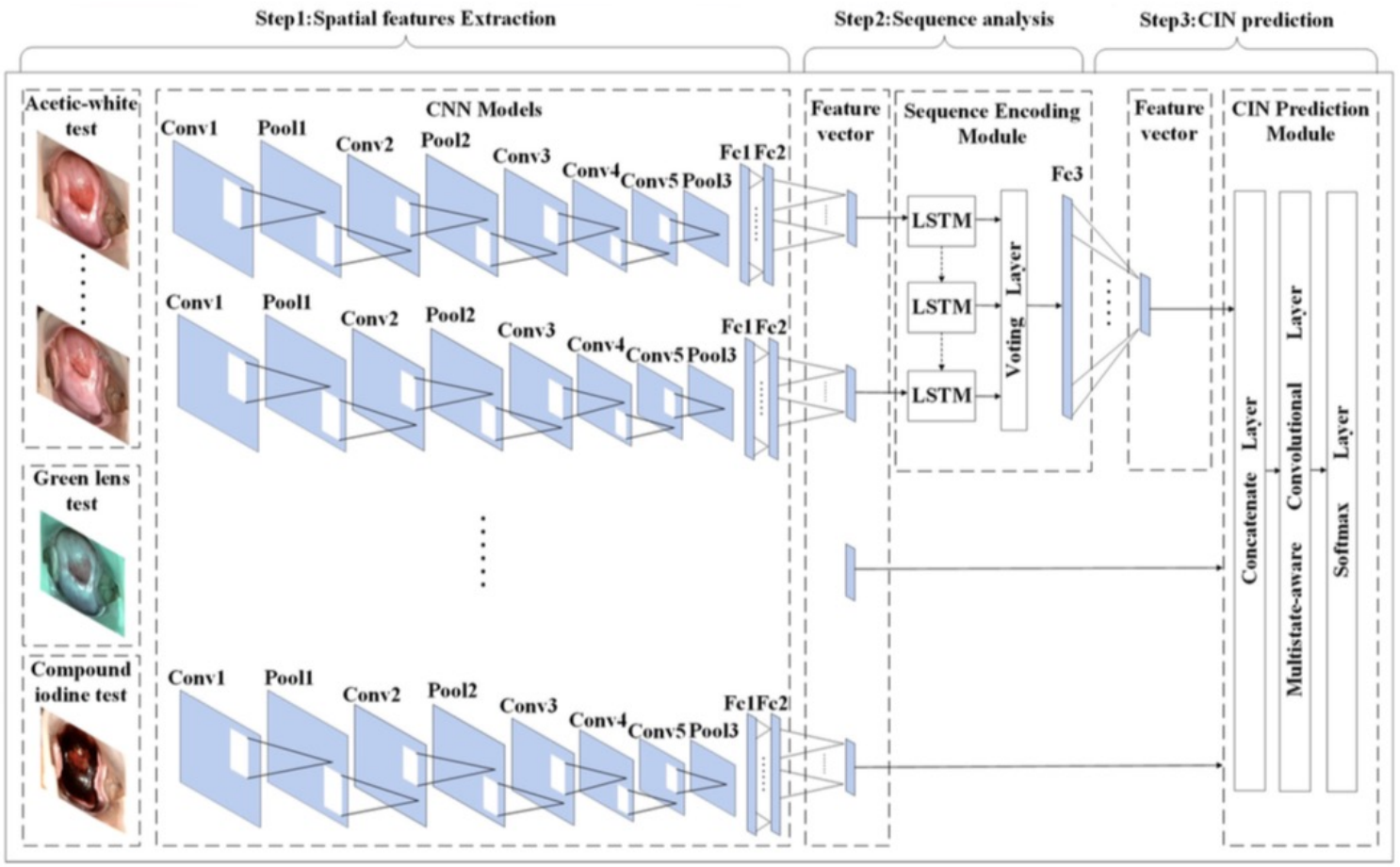
Automatic CIN Grades Prediction of Sequential Cervigram Image Using LSTM With Multistate CNN Features

679 patientes
4753 images



Yue et al., 2020

Automatic CIN Grades Prediction of Sequential Cervigram Image Using LSTM With Multistate CNN Features



Se : 95.7%
Sp : 98.7%

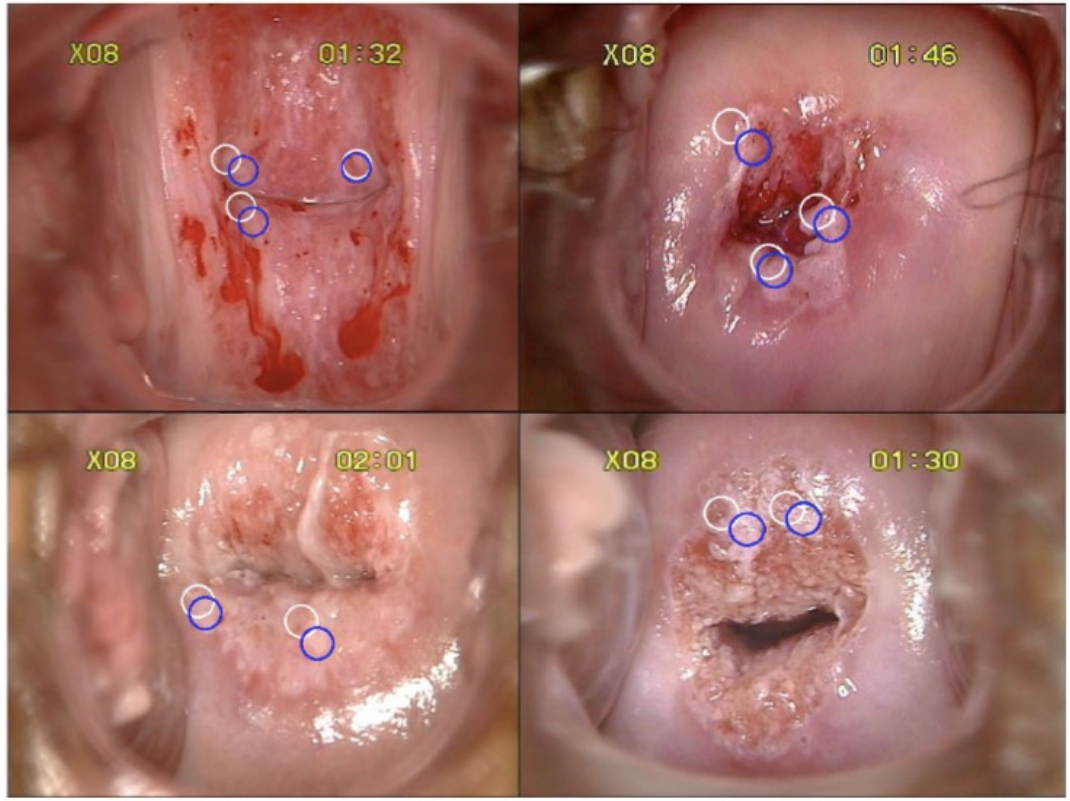
BMC Medicine

Development and validation of an artificial intelligence system for grading colposcopic impressions and guiding biopsies

19000 patientes

Détection des zones de HG et + :

- meilleur Sensibilité de l'IA / humain ($p<0.001$)
- spécificité identique

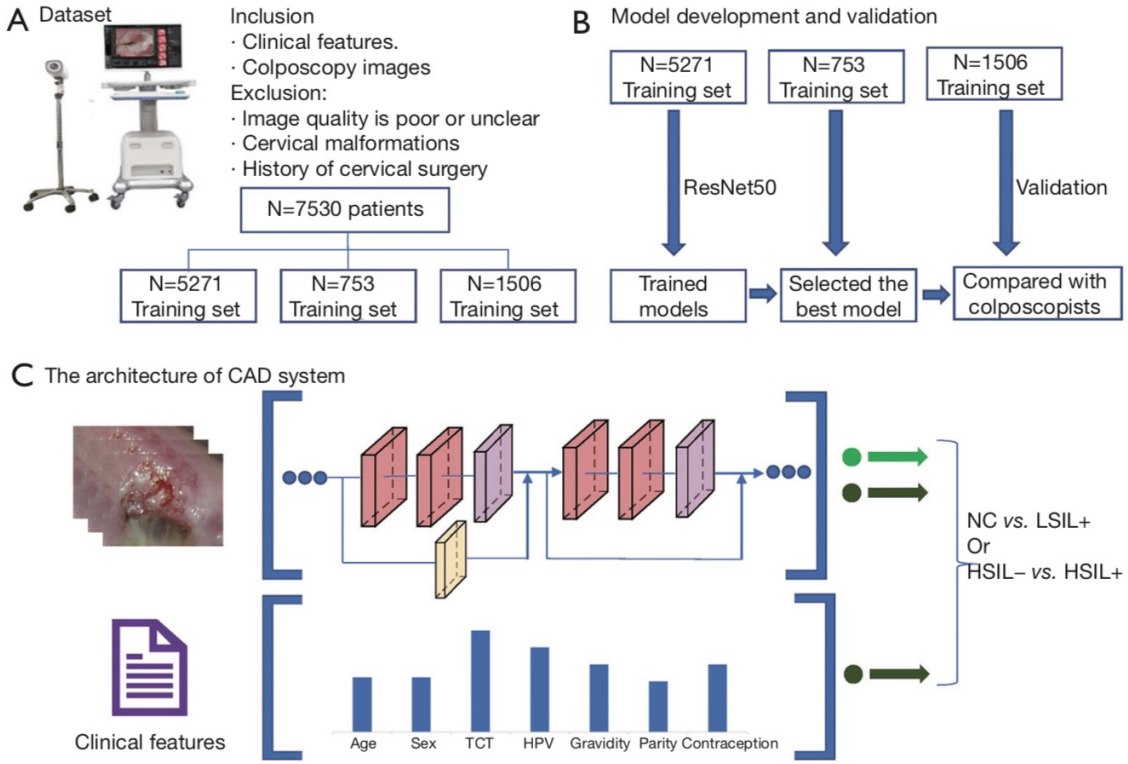


Xue et al., 2020

ATM | ANNALS OF TRANSLATIONAL MEDICINE

Computer-aided diagnostic system based on deep learning for classifying colposcopy images

7530 patientes
> 15000 images



Clinicien : Se 64%. Spe 71%
IA : Se 94%. Spe 87%

Liu et al., 2020

ATM | Annals of Translational Medicine

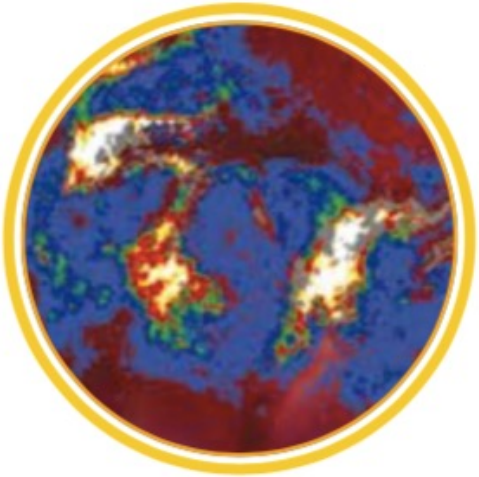
Computer-aided diagnostic system based on deep learning for classifying colposcopy images

Table 6 Comparison with colposcopists

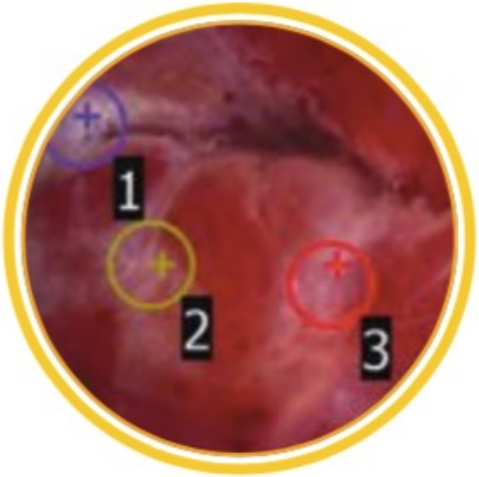
Task	Model	Accuracy	Sensitivity	Specificity	PPV	NPV
NC *vs.* LSIL+	CAD	0.883 (0.841–0.917)	0.954 (0.904–0.983)	0.827 (0.762–0.881)	0.812 (0.742–0.871)	0.959 (0.912–0.985)
	Senior	0.857 (0.812–0.894)	0.924 (0.865–0.963)	0.803 (0.735–0.861)	0.787 (0.714–0.849)	0.931 (0.877–0.966)
	Junior	0.750 (0.697–0.798)	0.886 (0.819–0.935)	0.642 (0.565–0.715)	0.661 (0.586–0.730)	0.878 (0.807–0.930)
HSIL– *vs.* HSIL+	CAD	0.810 (0.761–0.853)	0.828 (0.732–0.900)	0.803 (0.743–0.854)	0.632 (0.536–0.720)	0.919 (0.870–0.954)
	Senior	0.833 (0.786–0.874)	0.448 (0.341–0.559)	0.991 (0.966–0.999)	0.951 (0.835–0.994)	0.814 (0.762–0.860)
	Junior	0.757 (0.704–0.804)	0.195 (0.118– 0.294)	0.986 (0.959–0.997)	0.850 (0.621–0.968)	0.750 (0.695–0.799)

Liu et al., 2020

DYSIS



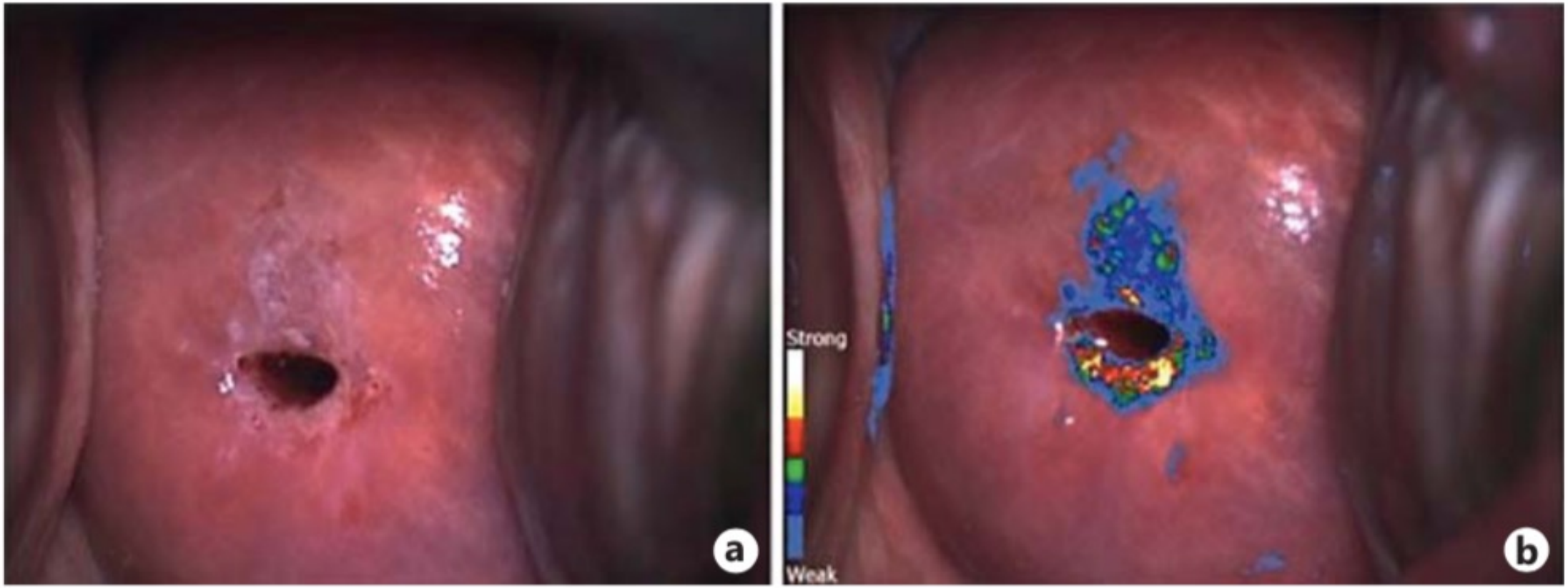
MAPPING



MARQUEURS

SUIVI PATIENT

DYSIS



Digital Colposcopy With Dynamic Spectral Imaging for Detection of Cervical Intraepithelial Neoplasia 2+ in Low-Grade Referrals: The IMPROVE-COLPO Study

JOURNAL OF Lower Genital Tract Disease

DYSIS

Outcome	Retrospective	Prospective	Difference*
All ages	1,788	1,857	
CIN 2+			
True-positive patients	129	176	
True-positive rate	7.21%	9.48%	2.27% (p = .014)
CIN 3+			
True-positive patients	37	60	
True-positive rate	2.07%	3.23%	1.16% (p = .031)
Age ≥30 y	1,161	1,234	
CIN 2+			
True-positive patients	73	117	
True-positive rate	6.29%	9.48	3.19% (p = .004)
CIN 3+			
True-positive patients	21	44	
True-positive rate	1.81%	3.57%	1.76% (p = .008)

Conclusion

Nombreuses techniques

Augmentation Se / Sp (?)

A développer +++ (tests combinés)

Conclusion

Mais…

Importance de la formation ET pratique régulière +++

Charte de qualité SFCPCV

Merci pour votre attention