

Departamento Ingeniería
Eléctrica

Presentation Title

Presentation Subtile

February 22, 2019

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Pathological examination issues

- Due to the heterogeneity of the disease most of the morphological indicators of prognosis are not quantified

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- Due to the heterogeneity of the disease most of the morphological indicators of prognosis are not quantified
- Subjective observations are susceptible to inter and intra observer variations **Imagenes con kappa**

The Suitability of a Quantitative Estimation

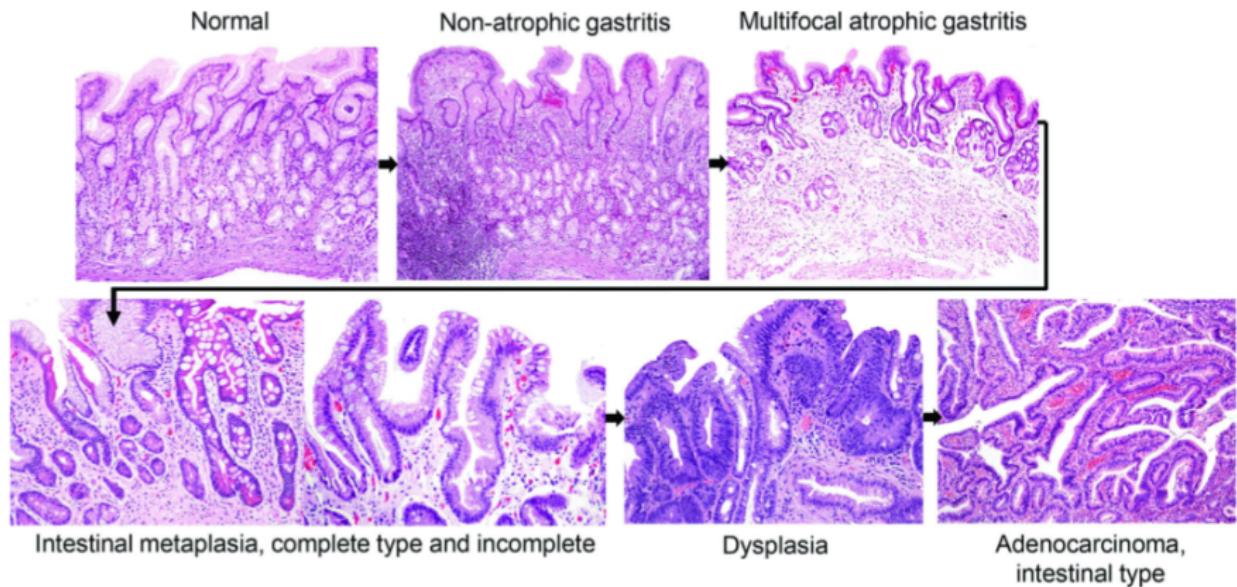
- Digital version of whole glass slide and image analysis are using to improve the diagnosis

The Suitability of a Quantitative Estimation

- Digital version of whole glass slide and image analysis are using to improve the diagnosis
- The Quantification of morphological structures to determine the predisposition of a disease and to deliver healthcare **imagenes??**

Quantification of Premalignant Lesions of the Gastric Mucosa - 1st case of Study

Changes of the Normal Mucosa to Adenocarcinoma

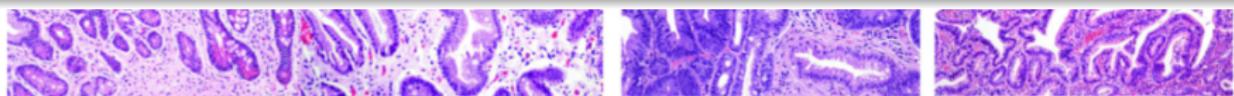


Correa's Cascade of Gastric Carcinogenesis; 1976

Changes of the Normal Mucosa to Adenocarcinoma



Some studies suggest that the cancer progression could not follow this sequence!



Intestinal metaplasia, complete type and incomplete

Dysplasia

Adenocarcinoma,
intestinal type

Correa's Cascade of Gastric Carcinogenesis;1976

The Carcinogenesis Cascade Main Concerns

- Diffuse type of gastric cancer are not related with atrophy or metaplasia (Lauren classification)

¹ Stolte M, Zeitschrift für Gastroenterologie, 1992

² Filipe ML, International Journal of Cancer, 1994

³ Hattori T., Cancer 1986

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- In the non-atrophic gastritis foci of intestinal metaplasia are found¹
- Metaplasia grade I and II have been show no risk for cancer progression²
- Dysplasia are not found in micro-early carcinomas (*Diameter < 5mm*)³

⁴

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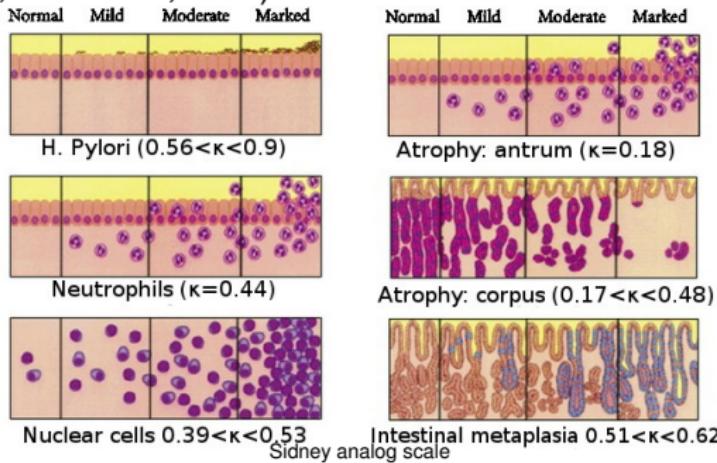
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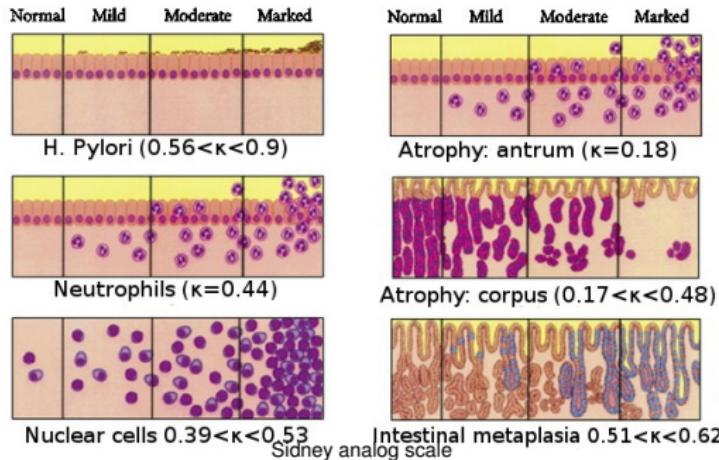
Inter-observer Variability

- A highly disagreement between experts reported using kappa coefficient (Aydin,2003;Offerhaus,1999)



Inter-observer Variability

- Kappa coefficient measure the agreement between observers, $\kappa = 0$ corresponds to a bad agreement; $\kappa = 1$ corresponds to a good agreement



Processes involved in GCa incidence are not understood, and the current grading scales are expert dependent, A Careful and reliable measurement of histological features may prevent further malignant outcomes^{56 7 8}

⁵Tepes,2004

⁶Sipponen P.,1994

⁷Meining A,2001

⁸Correa P., 1992

Hypothesis

An accurate quantification of the tissue structures will allow finding a suitable characterization of the disease

Objectives

General Objective:

To formulate an automatic model to find and quantify patterns in gastric premalignant lesions in histological images of the gastric mucosa to the different degrees of atrophy and intestinal metaplasia

Contribution

- The proposal consists in highlighting the importance of an exact measurement in gastric premalignant lesions and the possibility of using this in the pathology workflow.

Expected results

- Different strategies to establishes the stage in PGC lesions
- A computer-aided system to be applied by a pathologist in the workflow

Materials and Methods

Materials

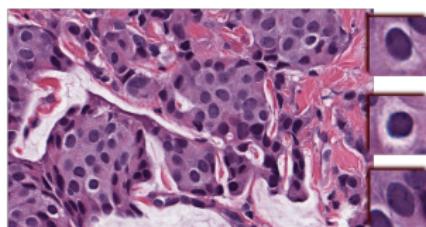
- TCGA Gastric cancer open database with 771 whole slide images and 443 of this with their histological description
- A temporal cohort of histological images with PGC from Urkunina 5000 project
- 30 GCa cases from Universidad Nacional de Colombia

Second case of Study

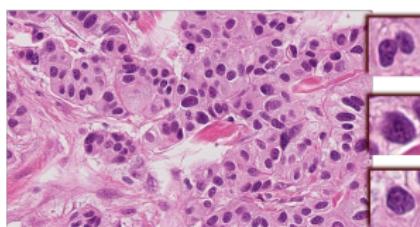
Nuclear Pleomorphism (NP) - The Suitability of a Quantitative Estimation

Nuclear Pleomorphism in BC

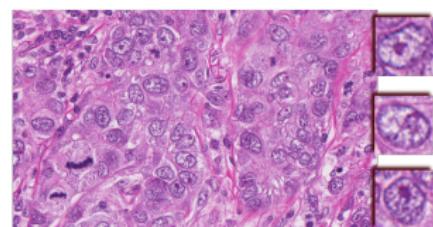
- Researching in automatic quantification strategies for nuclear pleomorphism in breast cancer(NPBca).



grade 1



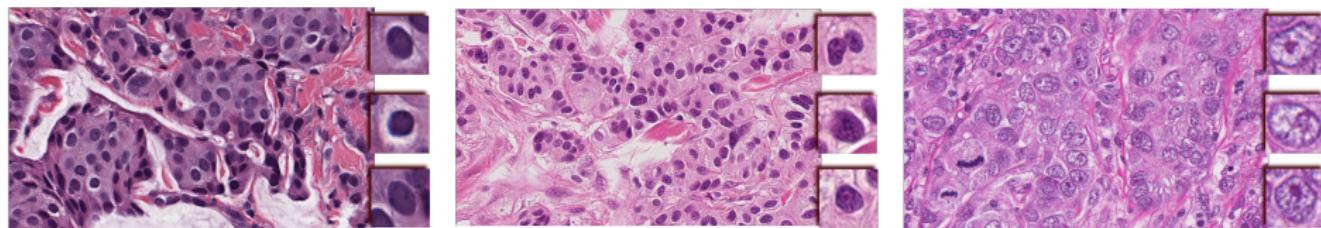
grade 2



grade 3

Nuclear Pleomorphism in BC

- Researching in automatic quantification strategies for nuclear pleomorphism in breast cancer(NPBca).
- NPBca is an indicator of the aggressiveness of the disease



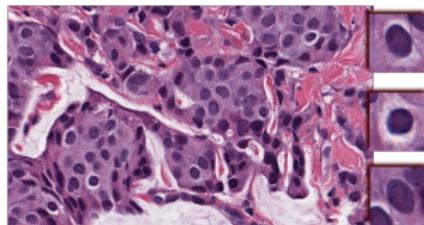
grade 1

grade 2

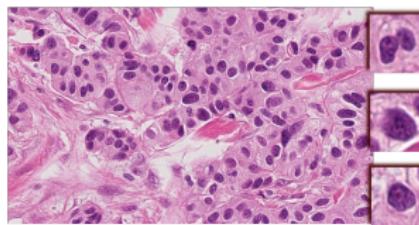
grade 3

Nuclear Pleomorphism in BC

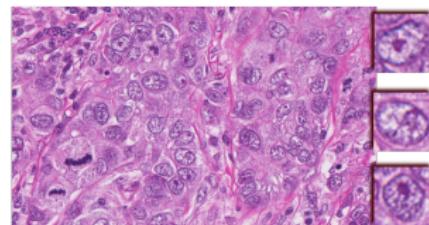
- Researching in automatic quantification strategies for nuclear pleomorphism in breast cancer(NPBca).
- NPBca is an indicator of the aggressiveness of the disease
- A low inter-observer agreement ($0.3 < \kappa < 0.5$)



grade 1

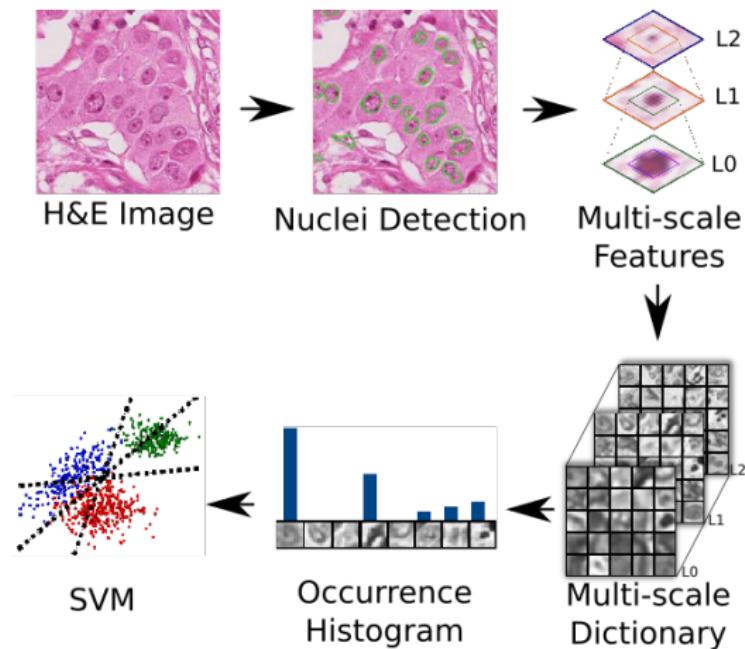


grade 2

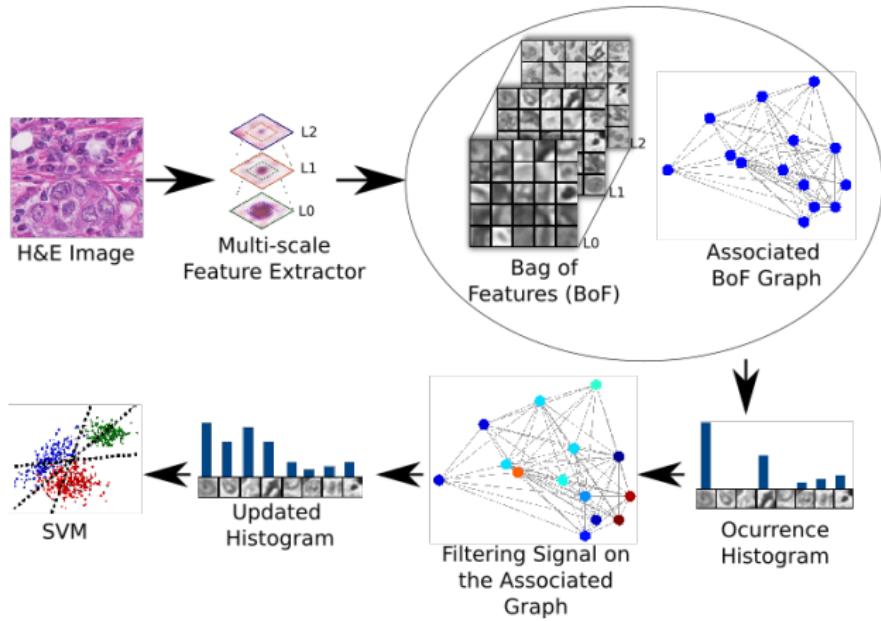


grade 3

Previous: A Bag of Features Based Strategy



Previous: A Bag of Features onto a Graph Strategy



Research Products

- Moncayo, R., Romo-Bucheli, D., Romero, E. **A Grading Strategy for Nuclear Pleomorphism in Histopathological Breast Cancer Images Using a Bag of Features (BoF)**. In Progress in Pattern Recognition, Image Analasys, Computer Vision and Applications, Pages 75-82, november 2015. ISBN 978-3-319-25751-8
- Romo-Bucheli, D., Moncayo, R., Cruz, A., Romero, E., **Identifying histological concepts on basal cell carcinoma images using nuclei based sampling and multi-scale descriptors**. In 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI), April 2015, pages 1008-1011, ISSN 1945-7928
- Moncayo, R., Romo-Bucheli, D., Arias, V., Romero, E., **Scoring Nuclear pleomorphism using a visual BoF modulated by a graph structure**, In the 13th International Symposium on Medical Information Processing and Analysis, October 2017

The Next Step

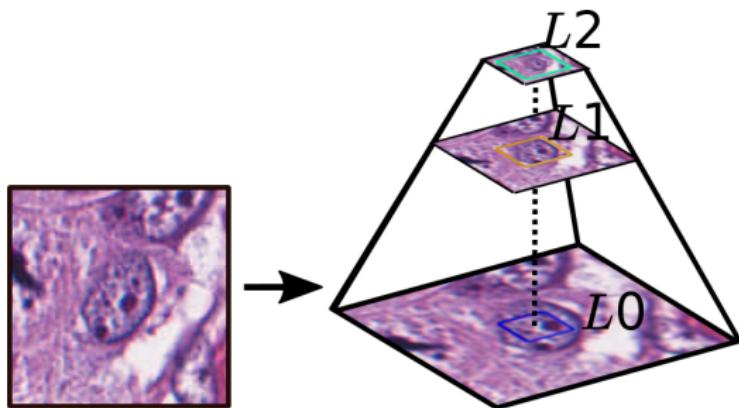
The use of nuclear pleomorphism grade would be correlated with the patient outcome resulting in a reliable measure for the patient

Materials

Coming soon...

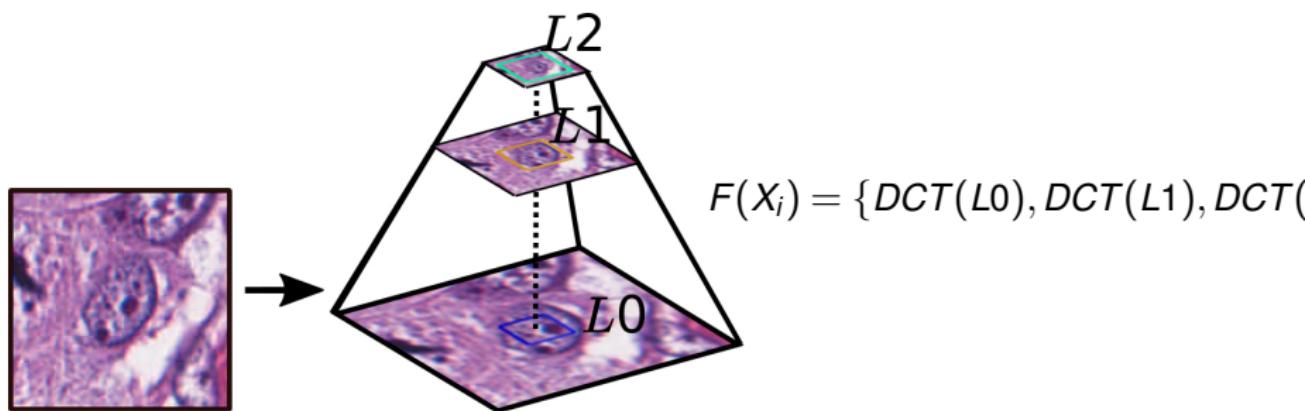
Multi-scale Features

- Each nucleus candidate is represented by multiple scales characterized by the discrete cosine transform (DCT) using enough coefficients to reconstructing the original image
- The coefficients from different scales are concatenated into a single feature



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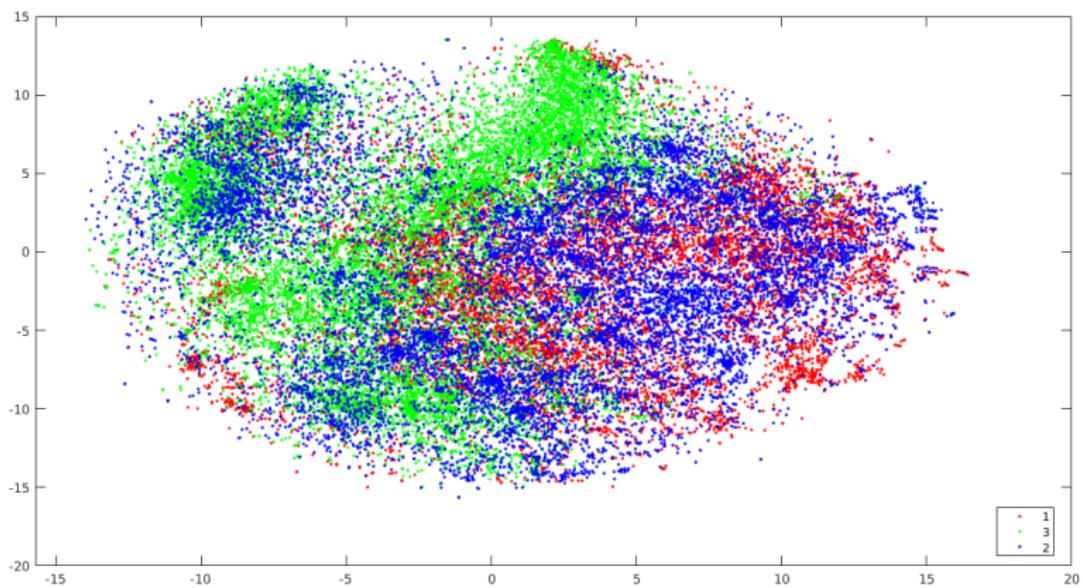
Probabilistic Latent Semantic Analysis(PLSA)

- Each multiscale representation is used as a **document** for build a PLSA model to find some topics

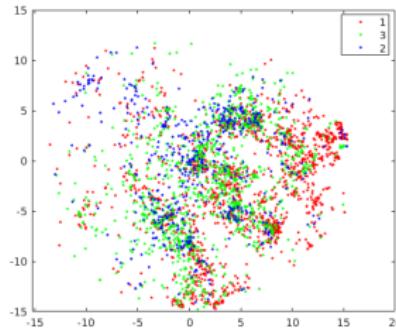
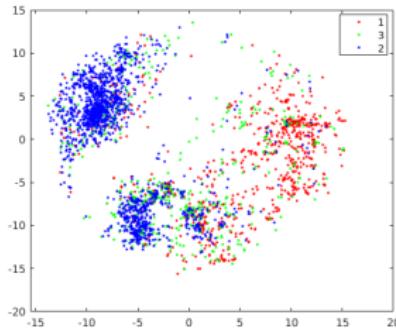
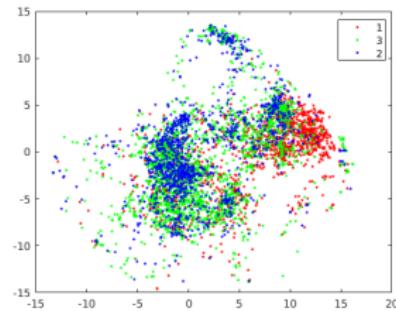
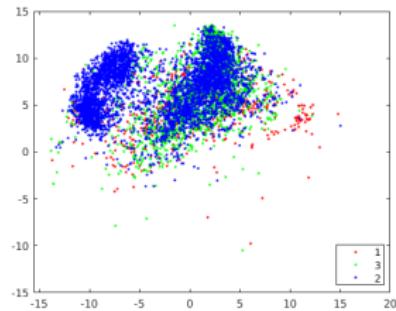
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- Each multiscale representation is used as a **document** for build a PLSA model to find some topics
- T-sne is used to visualize the original space and the PLSA generated

Visual Results - Original Space



Visual Results - Space by topic



Research Group



The Computer Imaging and Medical Applications Laboratory (CIM@LAB) is a research group devoted to solve pertinent medical problems by combining artificial vision and machine learning techniques.

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Director: Ph.D Eduardo

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Professors: 2

Doctoral Students: 9

Master Students: 19

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Finished PH.D. thesis: 9

Finished M.Sc. thesis:
46

International indexed journals: 37

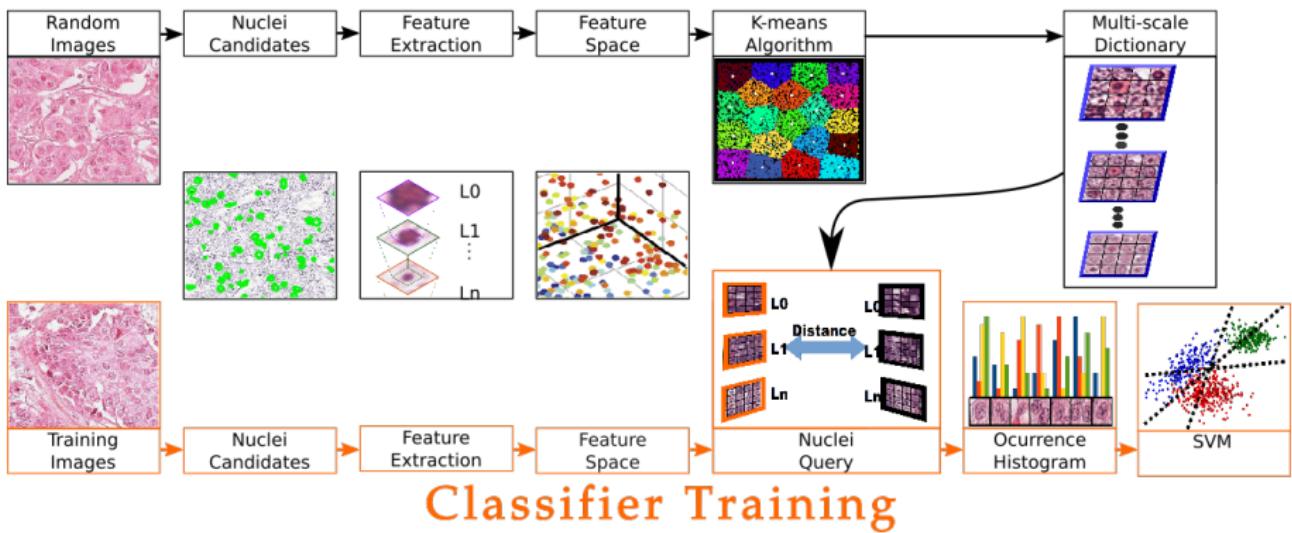
International peer reviewed conferences:
100

Books & chapters: 8

Colombian journals: 15
Colombian conferences: 21

First Aproach

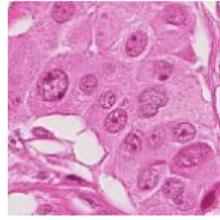
Dictionary Building



Classifier Training

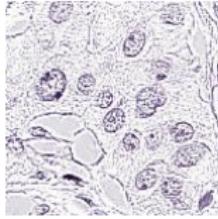
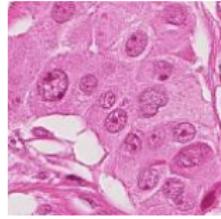
Nuclei Detection

- Using a color deconvolution technique the Hematoxylin (H) and eosin (E) stains are estimated



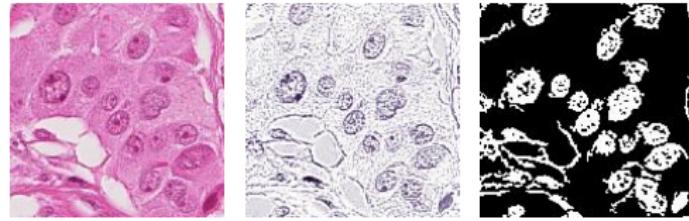
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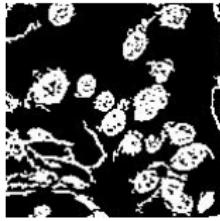
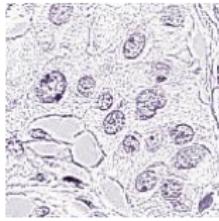
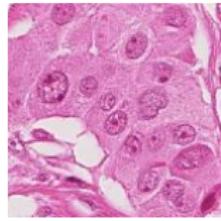
Nuclei Detection

- Using a color deconvolution technique the Hematoxylin (H) and eosin (E) stains are estimated
- Watershed algorithm is used to detect nuclei candidates in H stain



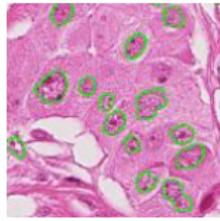
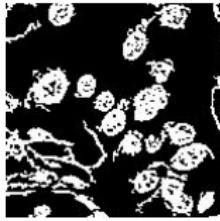
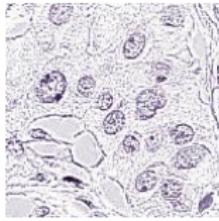
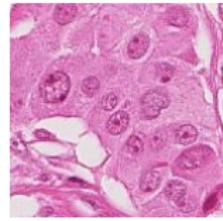
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- Final candidates are found after morphological operations



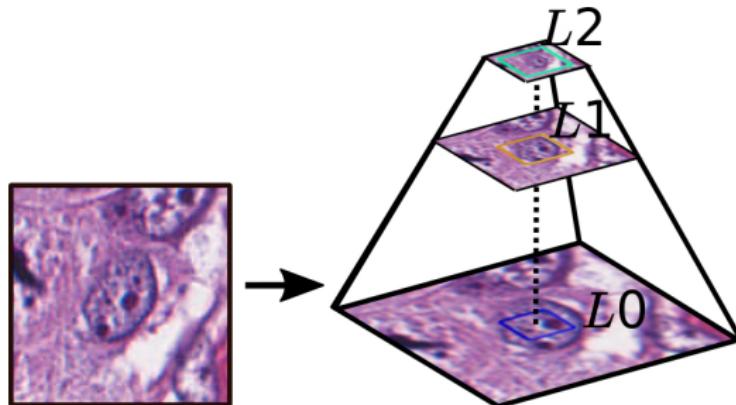
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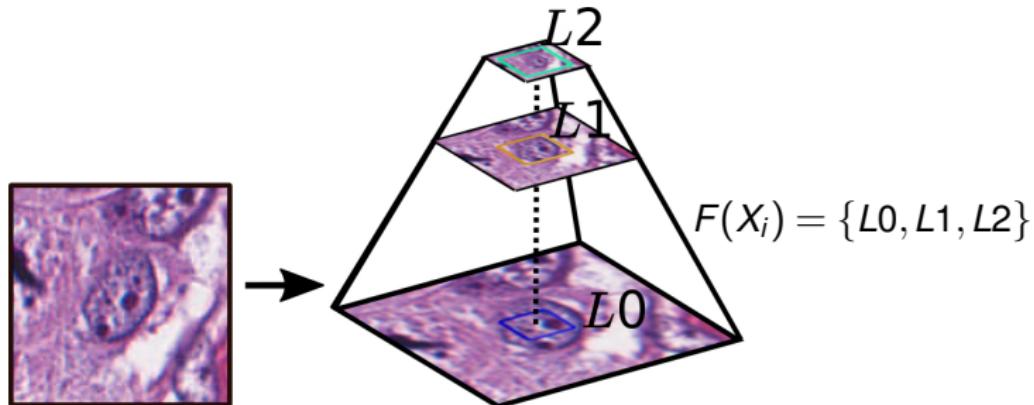
Multi-scale Feature Extractor

- The characterization of each nucleus candidate was performed by analyzing multiple scales



Multi-scale Feature Extractor

- The characterization of each nucleus candidate was performed by analyzing multiple scales
- The feature vector corresponds to the information from RGB patches which are concatenated along one dimension.



Results F1-Score

The F-score is used to evaluate the classification

$$F_{\beta} = (1 + \beta^2) \cdot \frac{\text{precision}.\text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}} \quad (1)$$

$\beta = 1$ is used this is the harmonic mean between precision and recall

Dataset - Mitos Atypia 14

| Grade | #40X images |
|-------|-------------|
| NP 1 | 92 |
| NP 2 | 900 |
| NP 3 | 208 |

Table: *Training and validation - 11 cases for training*

| Grade | # 40X images |
|-------|--------------|
| NP 1 | 152 |
| NP 2 | 252 |
| NP 3 | 92 |

Table: *Test dataset - 5 cases*

Results

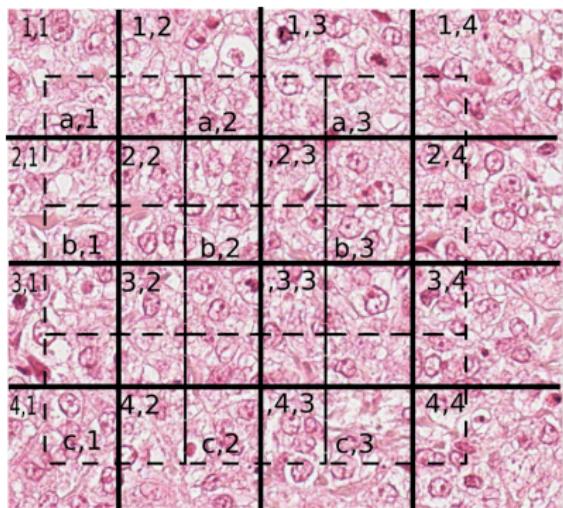
| Experiment/S.Patch | 32x32 L2 | 20x20 L2 |
|--------------------|---------------|---------------|
| 1 vs 2 and 3 | 0.593 | 0.434 |
| 3 vs 1 and 2 | 0.642 | 0.47 |
| 1 vs 2 | 0.7128 | 0.47 |
| 1 vs 3 | 0.660 | 0.7029 |
| 2 vs 3 | 0.6759 | 0.5813 |

Table: *Results Bag Of Features*

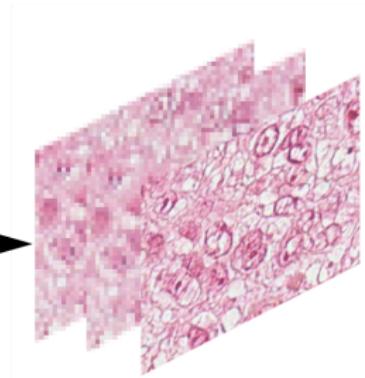
Current Work

- **To enhance the automatic nuclear pleomorphism grading**
- To find out if there is a relationship between the nuclear grade quantification with the cancer recurrence

CNN Framework

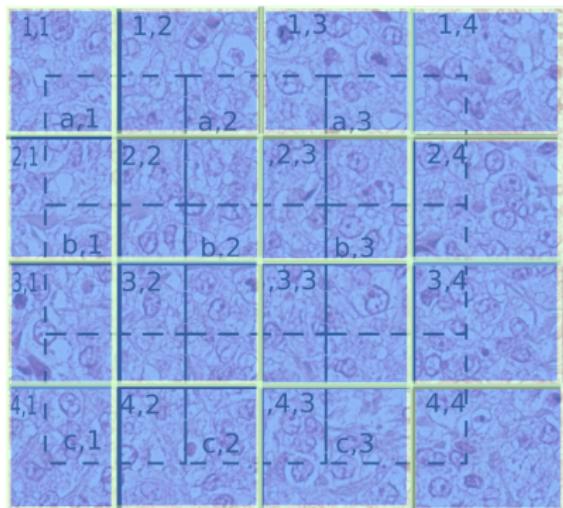


Flip,
Rotations,
color

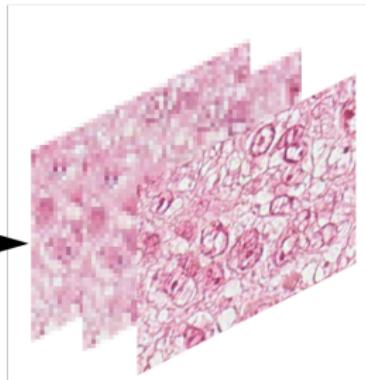


CNN

CNN Framework



Flip,
Rotations,
color



CNN

[V_{1,1}, V_{1,2} ..., V_{4,4}]



Classifier

Dataset- Mitos Atypia 14

| Grade | #40X images | Total Patches 344x344 pixels | Train | Validation |
|-------|-------------|---------------------------------|--------|------------|
| NP 1 | 92 | 21,344 | 18,144 | 3,200 |
| NP 2 | 900 | 22,500 | 19,096 | 3,404 |
| NP 3 | 208 | 20,800 | 17,764 | 3,036 |

Table: *Training and validation - 11 cases for training*

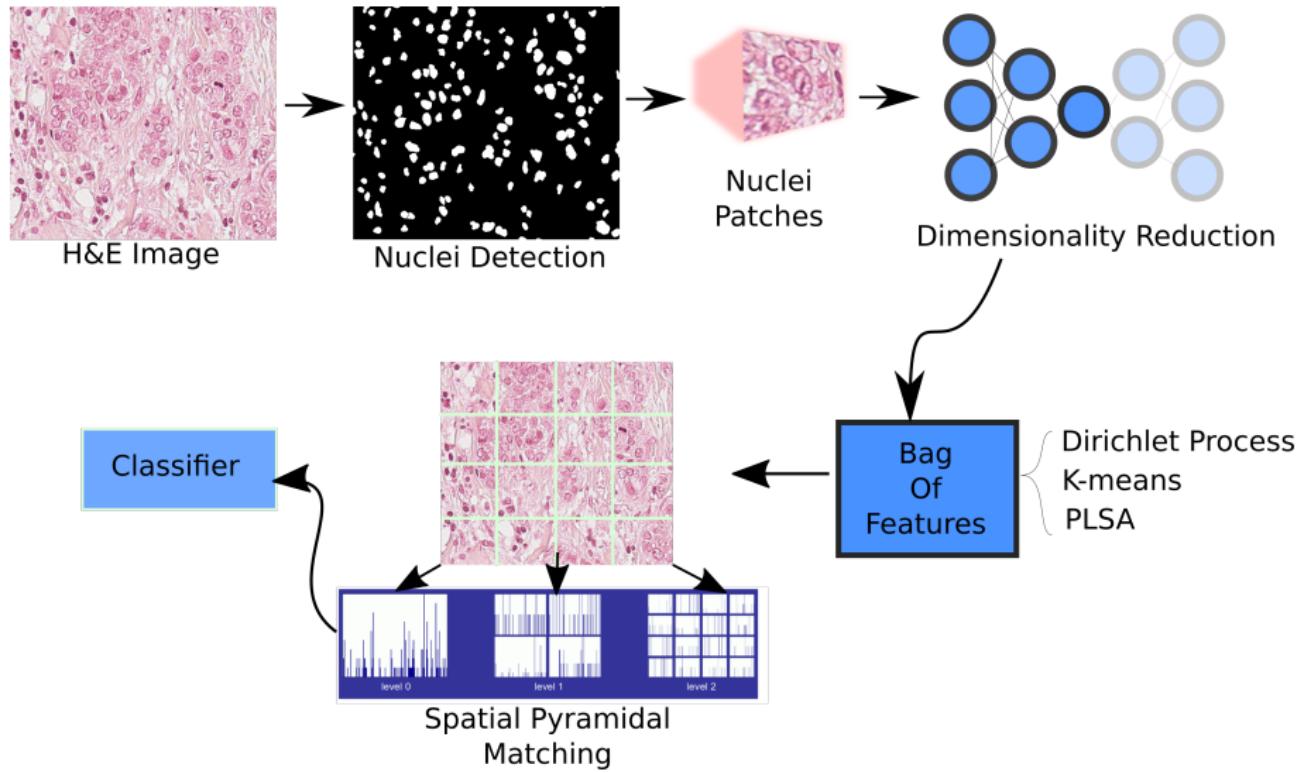
| Grade | # 40X images |
|-------|--------------|
| NP 1 | 152 |
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| NP 3 | 92 |

Table: *Test dataset - 5 cases*

Results

| | CNN (1024dim) | CNN (3dim) | VGG16 | Alexnet | Resnet50 |
|----------------|------------------|---------------|-------|---------|--------------|
| 3Vs.1 and 2 | 0.635 | 0.523 | 0.629 | 0.493 | 0.685 |
| 1Vs.2 and 3 | 0.676 | 0.645 | 0.564 | 0.581 | 0.573 |
| 1 Vs 2 | 0.637 | 0.664 | 0.453 | 0.623 | 0.592 |
| 2 Vs 3 | 0.570 | 0.567 | 0.544 | 0.619 | 0.670 |
| 1 Vs 3 | 0.666 | 0.672 | 0.620 | 0.649 | 0.563 |

Spatial Pyramidal Characterization

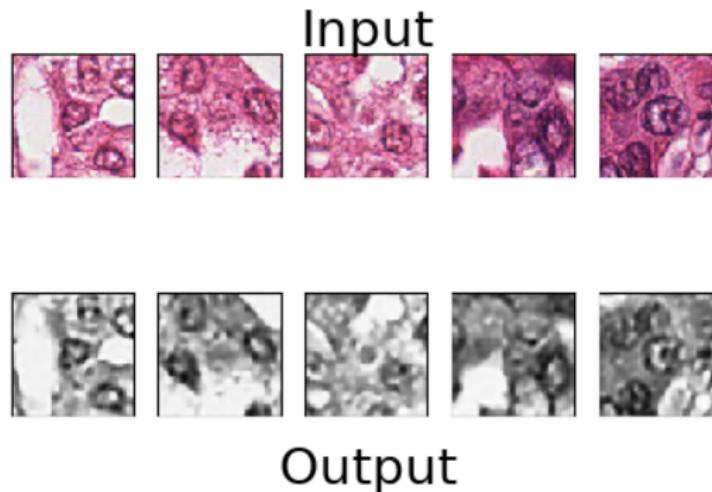


Nuclei Detection

- Color deconvolution to find hematoxylin channel (Macenko et al.)
- Watershed Algorithm to find connected components at different scales (Veta et al.)
- Patches are extracted using the nuclei centroid as seed (72x72 pixels)

Dimensionality Reduction- Convolutional autoencoder

- 3 convolutional layer for encoding and 3 for decoding
- 2048 dimensions in coded representation for nuclei (22.5 compression factor)
- 6300 dim feature vector (L0,L1,L2)



Autoncoder Reconstruction

Results

| | PS. | PS L0 | PS L01 | PS L2 | BOF PY | BOF PY L0 | BOF PY L1 |
|---------------|-------|--------------|--------|-------|--------------|--------------|--------------|
| 3 Vs. 1 and 2 | 0.578 | 0.630 | 0.565 | 0.53 | 0.624 | 0.593 | 0.583 |
| 1 Vs. 2 and 3 | 0.624 | 0.564 | 0.520 | 0.489 | 0.692 | 0.642 | 0.678 |
| 1 Vs 2 | 0.473 | 0.597 | 0.542 | 0.573 | 0.650 | 0.713 | 0.660 |
| 2 Vs 3 | 0.560 | 0.603 | 0.606 | 0.632 | 0.722 | 0.660 | 0.729 |
| 1 Vs 3 | 0.623 | 0.716 | 0.639 | 0.632 | 0.628 | 0.675 | 0.740 |

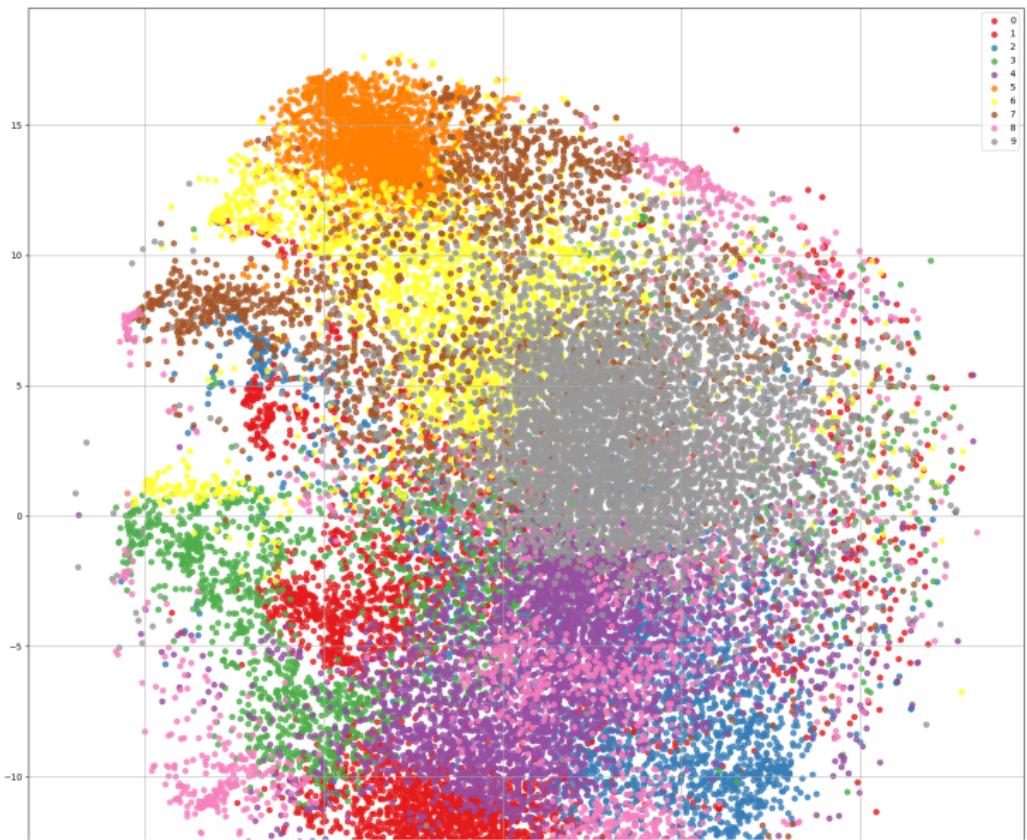
New Dataset

| Grading | # Marked Areas |
|--------------------|----------------|
| Grade 1 | 135 |
| Grade 2 | 132 |
| Grade 3 | 39 |
| Total Cases | 24 |

Final Remarks

- The Slightly variation between the NP grades and the high tissue variability makes difficult to find an adequate model.
- The CNN model could be improved if take advantage of the spatial information
- The auto-encoder representation and vocabulary construction maybe is not the most appropriate.

Thank you...



Proposed Grading Methodology

