VISION-BASED INSPECTION SYSTEM FOR ORNAMENTAL STONE USING A WEIGHTED HYBRID ENSEMBLE CLASSIFIER

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PRESENTER BIOGRAPHY

Liliana Antão is a **researcher in the Research Center for Systems & Technologies (SYSTEC)** since 2017, where she is responsible for developments in several **projects associated with Industry 4.0, mostly related to robotics and machine learning.**

She received a M.Sc. degree in **Electrical and Computer Engineering, specialization in Robotics** from **Faculty of Engineering, University of Porto** (FEUP) in 2017. She is presently a **PhD student in Informatics Engineering** in the same institution.

She is currently involved and has participated in **several European and national research projects funded by European Commission and FCT** (Portuguese Science Foundation), focused on **Machine Learning and Artificial Intelligence** with applications in the context of collaborative robotics.

CONTEXT

- **Ornamental Stone sector incorporating Industry 4.0** related practices/technologies in their production.
- **Several types of ornamental stone** are used such as marble, granite, limestone, among others.
- Ornamental stone **manufactured goods must satisfy specific aesthetic requirements** - 77% of companies in this sector **perform quality analysis via visual inspection.**
- **Subjective character** and the possible **incompatibility between the analyzes of different human inspectors** regarding the polishing quality of the finished surface.




CONTEXT

- **Inspection depends** on the **type of stone**, its mineral composition, and textural attributes.
- Such judgment **relies on human opinion and expertise**
- **Influenced by several characteristics**, such as mineral grains size, background color, cultural level of the human inspectors, and final destination of the stone manufactured goods.

- **Automated method to evaluate** the efficiency of the **polishing process** in ornamental stone.
- **Monitoring using sensors** is a common method, where **computer vision** is one of the **most versatile and cheap Non-Destructive Testing (NDT)** techniques.
- **Ensemble methods** proven to **improve performance**.

PROPOSED APPROACH

Vision-based inspection system to correctly classify ornamental stone slabs as defective or not:

- **Input:** image of the ornamental stone's slab
- **Image Pre-processing stage**
- **Weighted hybrid ensemble classifier**: classifier based on traditional image processing techniques (adaptive filters), ensembled with classifier based on a Convolutional Neural Network (CNN).
- Each predicted result is summarized by applying **a weighted voting scheme**, obtaining the result for that specific stone's surface.
- **Output:** OK (no or non-significant defects) or NOK (significantly defective).

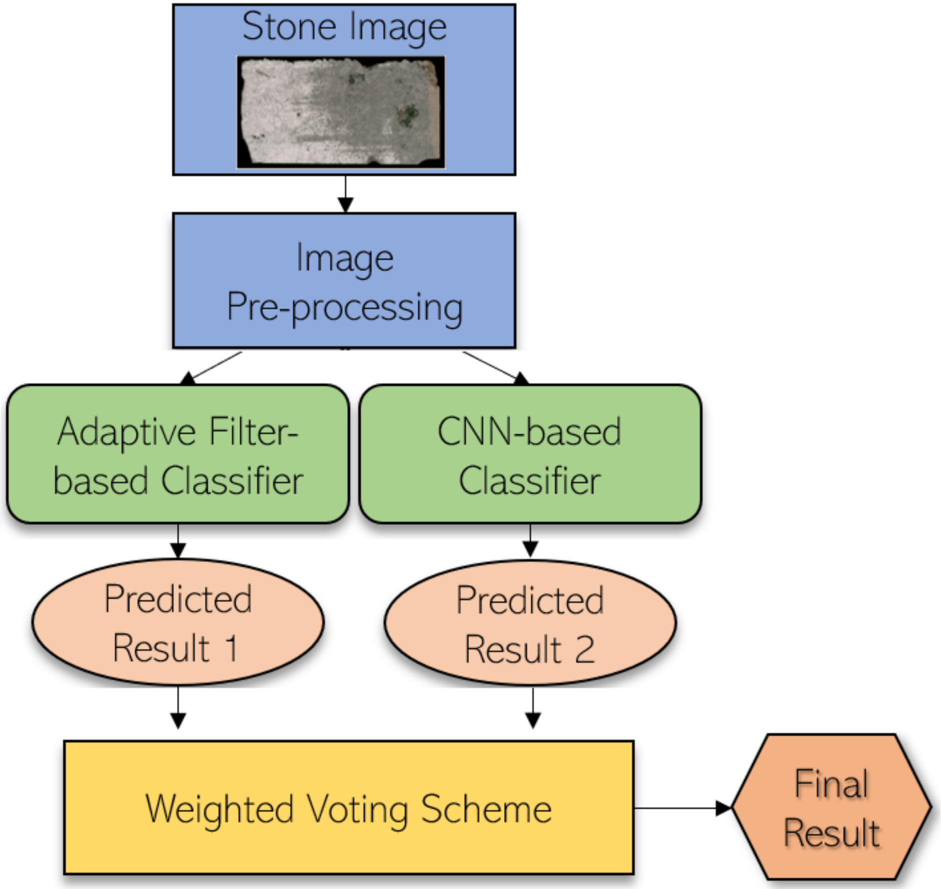
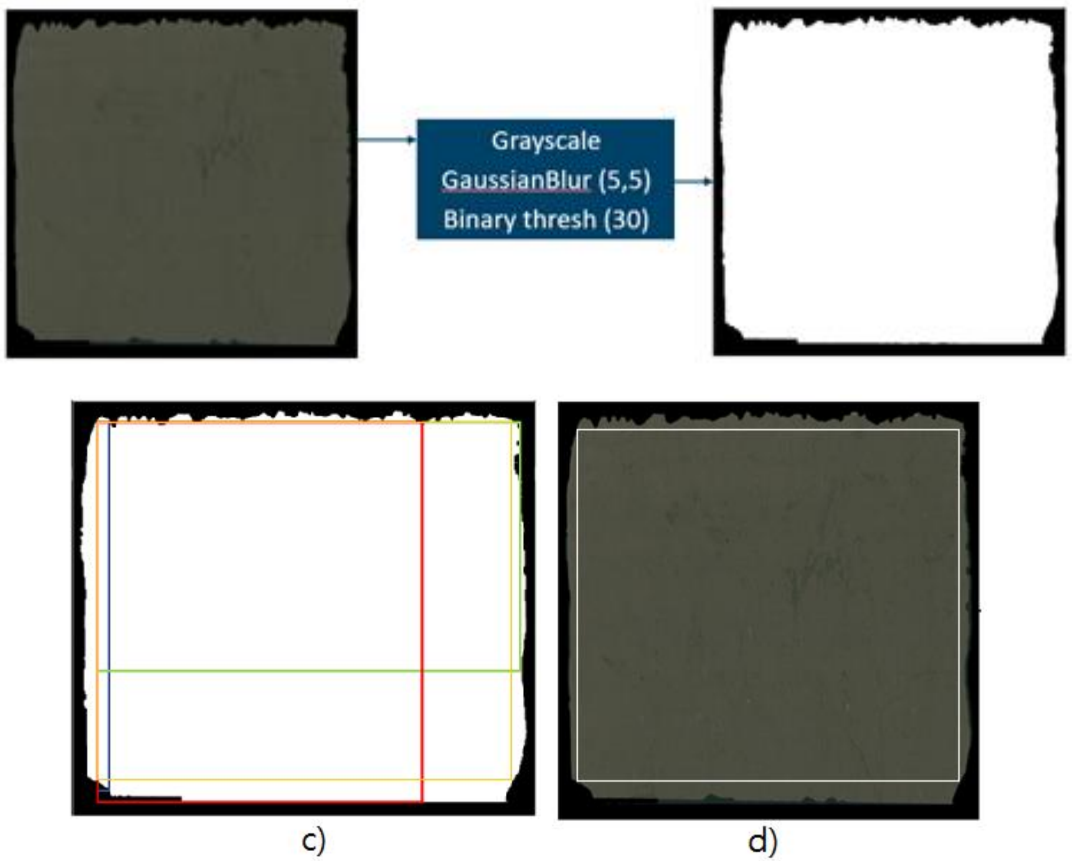


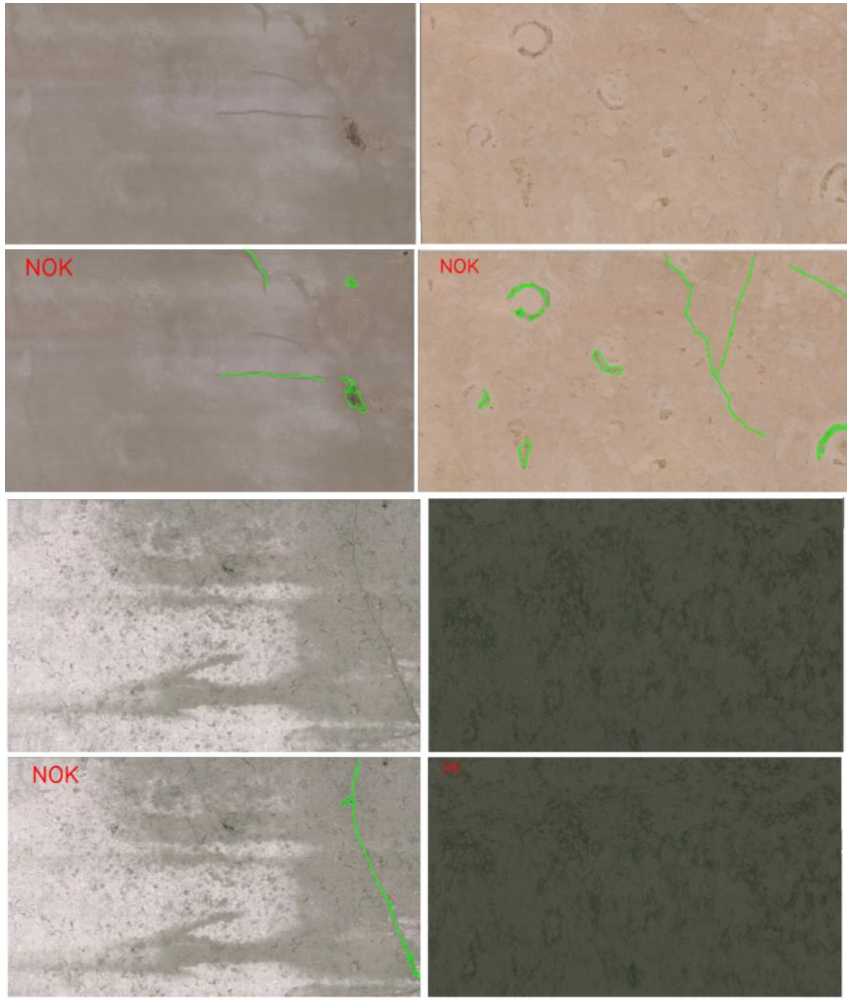
IMAGE PRE-PROCESSING STAGE

- Converts raw images into desired input; allows for a faster training, and better classifier performance.
- Grayscale, Gaussian filter and linear threshold.
- Simple approximation method used removes all redundant points and compresses the slab contours
- Contour's features evaluated, and the general external outlines of the stone obtained.
- Quadrilateral Region Of Interest (ROI): generate all rectangles that can be built using those pair of contour points, biggest without any portion of the background is chosen.



WEIGHTED HYBRID ENSEMBLE CLASSIFIER
Adaptive Filtering-based classifier

- **Adaptive Filtering-based classifier**: traditional image processing with statistical and structural adaptation in Python and OpenCV functions
- **Low cost, low level, and lightweight** approach
- **Valley-emphasis method for thresholding** – optimal threshold value is selected automatically using the images' gray-level histogram
- **Sobel filter**, followed by an **oriented non-maximal suppression** for edge detection - **detect boundaries between the base pattern and anomalies**
- **Morphological filters** to better identify the presence of defects: area, perimeter, and ratio of the defect's surface area in respect to the ROI



WEIGHTED HYBRID ENSEMBLE CLASSIFIER
CNN-based Classifier

Different classifiers considered: ≠ combinations of architecture blocks and hyperparameters. Search space composed as follows:

- **Encoders:** Densetnet121, Densetnet201, Inceptionv3, mobilenetv2, resenet50v2, resnet101v2 or inceptionresnetv2;
- **Pooling**: Average or max;
- **Number of dense layers**: Between 1 and 4;
- **Dense Units**: Range(Start=128, End=2048, step=128);
- **Dropout:** 0, 0.1, 0.2, 0.3 or 0.4;
- **Optimizers:** Adam, Rmsprop, Nadam or SGD;
- **Learning rate:** 0.01, 0.001 or 0.0001

Example of a set of hyperparameters	
Encoders	Densenet121
Pooling	Average
Number of dense layers	1
Dense Units	1024
Dropout	0,2
optimizers	nadam
Learning rate	0,001

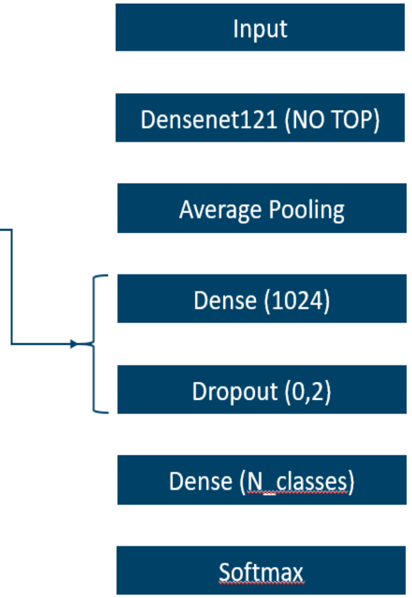


Figure - Example of a deep learning model using a combination of hyperparameters

WEIGHTED HYBRID ENSEMBLE CLASSIFIER
CNN-based Classifier

The model selection divided into 2 stages:

1) model elimination - models performing badly are eliminated, 10 best models with the lowest Average Validation Loss over three trains, are chosen
2) picks models from the 1st stage and checks their performances on the test dataset. Final model selected with the highest F1-score.

The **final model architecture** selected was:

- Encoder: Densetnet121
- Pooling: Average
- # of dense layers and dense units: 1, 1024
- Optimizers: Adam
- Learning rate: 0.0001

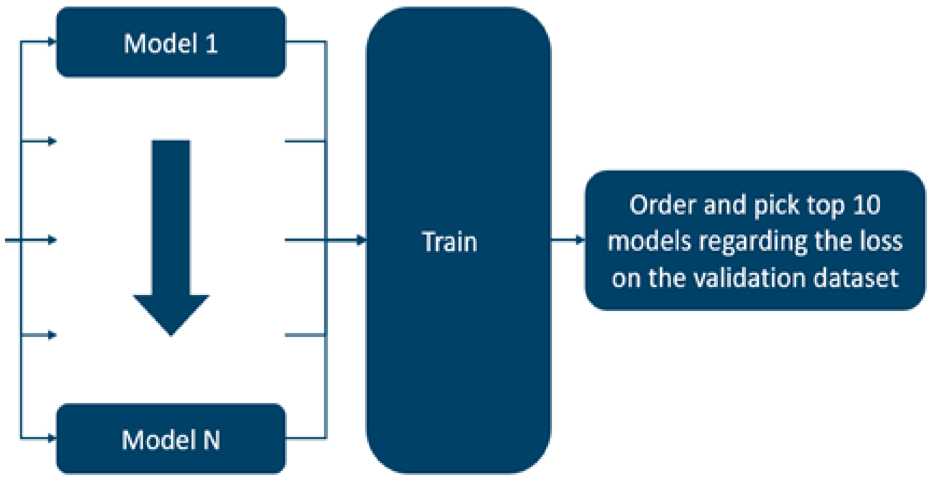


Figure: 1st stage of model selection

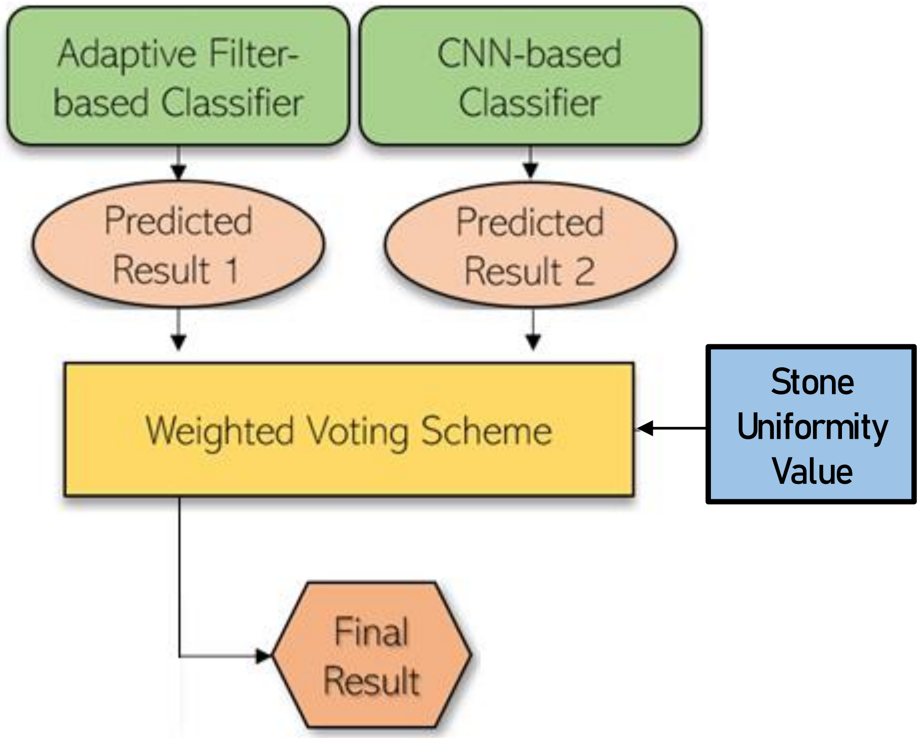
WEIGHTED HYBRID ENSEMBLE CLASSIFIER
Weighted Voting Scheme

- Each model's classification has a **different significance**.
- Criterion for weight setting: **stone surface's uniformity or lack of** is the characteristic with the most impact.
- Each trained classifier with **distinct weight according to performance in the validation set for each stone type**:

  - Highly uniform: 0.6 for Adaptive filter, 0.4 for CNN;

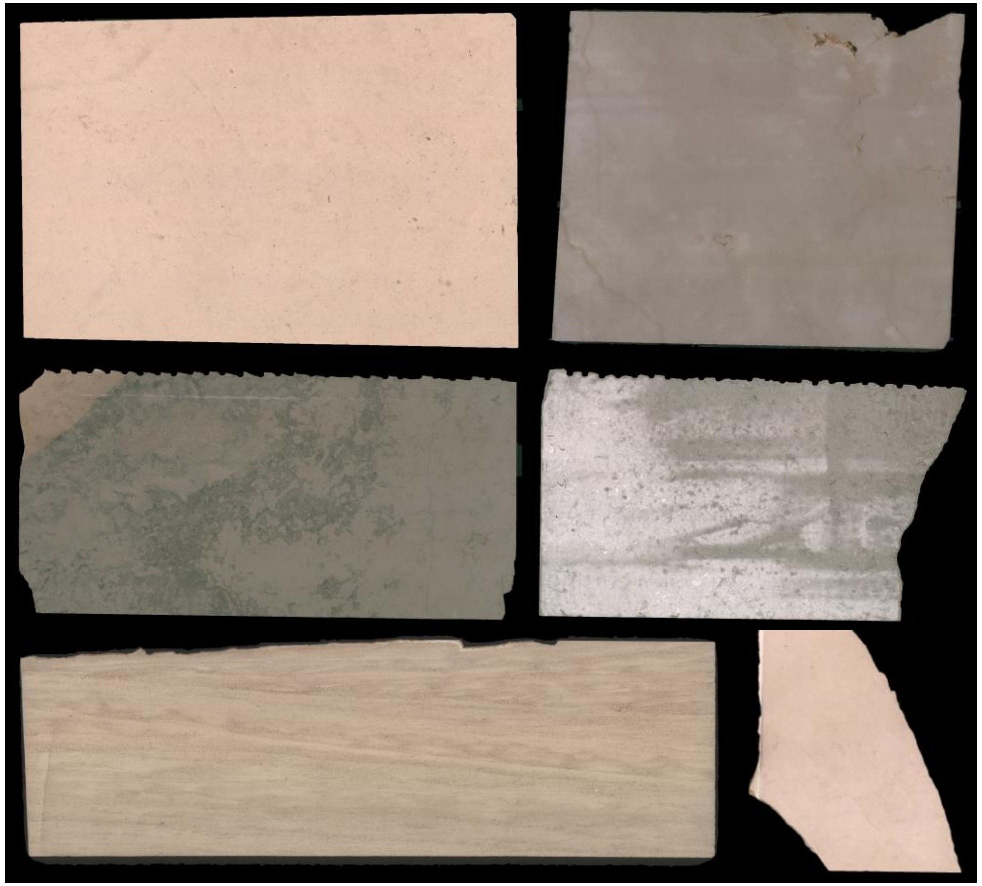
low uniformity: 0.7 CNN, 0.3 adaptive filter

- Final result based on the **highest weighted votes**.



SYSTEM VALIDATION
Dataset

- Limestone slabs' images collected after polishing process.
- **3 types of limestones**: Cadoico Azul Monica Silva (CADOICO), Salgueira Branco do Mar (SBM) and Salgueira Branco Real (SBR).
- **SBM, SBR: high homogeneity / uniformity** (uniformity< 9)
- **CADOICO: low uniformity / high heterogeneity** (uniformity>10).
- **954 images**: 707 normal and 247 as defective
- **Data augmentation** was performed by applying rotations to the original images with 90°, 180°, and 270°, resulting in a total of 3816 images
- Data divided into **70% training, 20% validation and 10% test**



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SYSTEM VALIDATION
Tests & Results

Model's performance highly impacted by this uniformity level - 3 variations of the dataset:

(a) augmented homogeneous dataset (SBM and SBR augmented data);

(b) augmented heterogeneous dataset (CADOICO augmented data);

(c) the complete augmented dataset (CADOICO, SBM, and SBR)

AUC as the main evaluation metric:

- **adaptive filtering classifier better for homogeneous stones**: difficulty with differentiating non-uniform patterns from defects, leading to false positives
- proposed **ensemble model maintains the best performance** from the isolated models, **except** in the **total dataset where the AUC is increased**

TABLE I
AUC ON THE DIFFERENT AUGMENTED DATASETS WITH ADAPTIVE FILTERING, CNN-BASED, AND HYBRID WEIGHTED ENSEMBLE CLASSIFIER.

Datasets	**(a) Homogeneous**	**(b) Heterogeneous**	**(c) Complete**
	AUC	*AUC*	*AUC*
Adaptive Filtering-based	96.91%	84.84%	88.42%
CNN-based	93.3%	93.2%	95.8%
Hybrid Weighted Ensemble	96.96%	93.2%	96.04%

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CONCLUSIONS & FUTURE WORK

i. Most of the polishing quality inspection performed manually by human experts - **inspection very subjective.**

ii. We propose an **automated monitoring system** based on **machine vision** to **assist human operators** with the quality of a polishing process.

iii. This monitoring system relies on a **weighted hybrid ensemble classifier**, which classifies polished ornamental stone slabs as **NOK or NOK**.

iv. Tests performed by using a **relevant dataset of images** collected after a **polishing process** - proposed approach outperforms isolated classifiers.

v. **Dataset limited** to limestone slabs from specific Portuguese region **- reduces the flexibility** of an automated monitoring approach.

vi. **Deploy and validate the solution in real polishing equipment** for real-time monitoring.

vii. **Add more input parameters to the system**: final destination of the stone manufactured good and the requirements from a specific client.

viii. Classification can later be used as feedback for **self-correction for the regulation/optimization of the polishing variables** and process parameters.

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Thanks!

Any questions?

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