PNEUMONIA DETECTION ° USING NON-LINEAR SVM

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SUPERVISED CLASSIFICATION OF X-RAY CHEST IMAGES



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SUPPORT VECTOR MACHINE

Linear and nonlinear



DATASET

X ray chest images



DATA PROCESSING

Image resize
Image Enhacement
Image Denoising



PERFORMANCE MEASURES

Accuracy - Precision Recall -F1- Score



SUPPORT VECTOR MACHINE





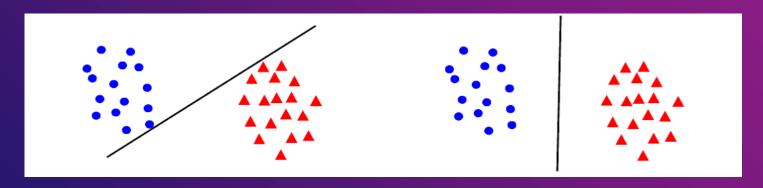
Linear and nonlinear

SVM

Let's assume that A and B are linearly separable sets, meaning there exists a hyperplane $H = \{ x \in R^n : w^T x + b = 0 \}$ such that

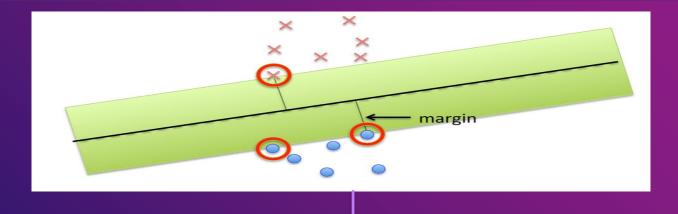
$$\begin{cases} w^T x + b > 0, & y_i = +1 \\ w^T x + b < 0, & y_i = -1 \end{cases} y_i (w^T x + b) > 0$$

The separating hyperplane is not unique.



SVM GOAL

Find the separating hyperplane that maximizes the distance between the closest training set and the separating hyperplane.

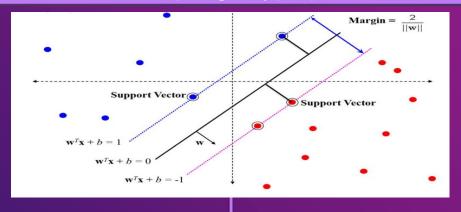


The distance from the closest training point is called the margin.

The circled points are called support vectors.

GEOMETRIC MARGIN

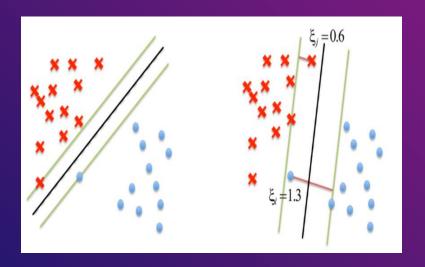
We define the optimal hyperplane (or maximum margin hyperplane) as: $(w*, b*) = \operatorname{argmax} \rho(w, b)$



The geometric margin between the two classes is $\frac{2}{\|...\|}$

The larger the margin (separation), the higher the expected generalization

Linear separability is generally too strong an assumption. However, the concept of an optimal separating hyperplane still makes sense, based on slack variables to handle outliers.



The ξi (Slack Variables) account for the nonseparability of the data.

 $\xi i = 0 \Rightarrow x_i$ correctly classified (outside the margin)

 $\xi i \in (0, 1) \Rightarrow x_i \text{ correctly classified (but within the margin)}$

 $\xi i > 1 \Rightarrow x_i$ misclassified (on the wrong side of the separating hyperplane))

C-SVM

Maximization of the (Soft) Margin and Minimization of the Number of Misclassified Samples

$$\min \frac{1}{2} \| w \|_2^2 + c \sum_{i=1}^n \xi_i$$

s.t.
$$y_i(w^T x + b) \ge 1 - \xi_i$$

 $\xi_i \ge 0$
Where $C > 0$

The regularization parameter C takes into account the penalty for misclassified data.

Larger C⇒ Fewer exceptions (smaller margin, potential overfitting).

Smaller C⇒ more eccezioni exceptions (larger margin, potential underfitting).

Non linear SVM

A classification problem of complex patterns thrown into a high-dimensional nonlinear space is more likely to be linearly separable than in a low-dimensional space. (Thomas Cover, 1965)

The goal is to project into high-dimensional space and solve with a linear model

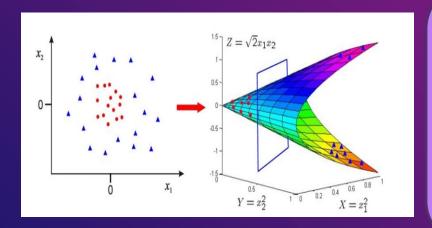


Mapping the data (input space) into a feature space of higher dimensions using a non-linear transformation $\Phi(x) \in R^{\wedge}p$ (p > n)

KERNEL

Applying SVM to $\Phi(x_i)$ rather than to x_i , such that the formulation of SVM (in the feature space) is expressed only using the inner product $(\Phi(x_i), \Phi(x_j))$. To achieve this, it is sufficient to know how to compute the scalar product $k(x_i, x_j)$ in the feature space.

k is called a kernel, and the same kernel can correspond to different feature maps Φ .



The idea of the kernel function is to perform operations in the input space rather than in the potentially high-dimensional feature space. Therefore, the inner product does not need to be evaluated in the feature space. We want the function to map observations from the input space to the feature space.







X ray chest images

DATASET



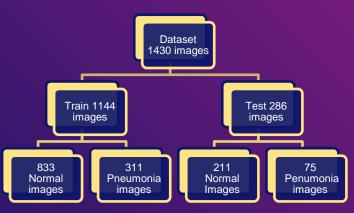
The dataset is organized into 2 different types (train and test) and contains various categories of images (Pneumonia/Normal). There are 1,430 chest X-ray images (JPEG) and 2 categories (Pneumonia/Normal).

For the analysis of chest X-ray images, all chest X-rays initially underwent a quality check, eliminating all low-quality or unreadable scans. The diagnoses of the images were then classified by two expert physicians before being authorized for model training.





DATASET SPLITTING



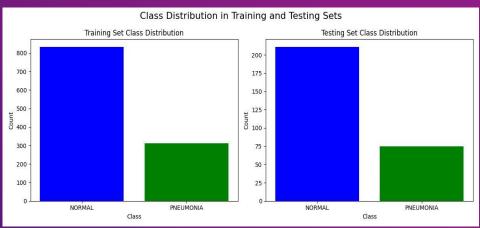


Image resize Image Enhacement Image Denoising







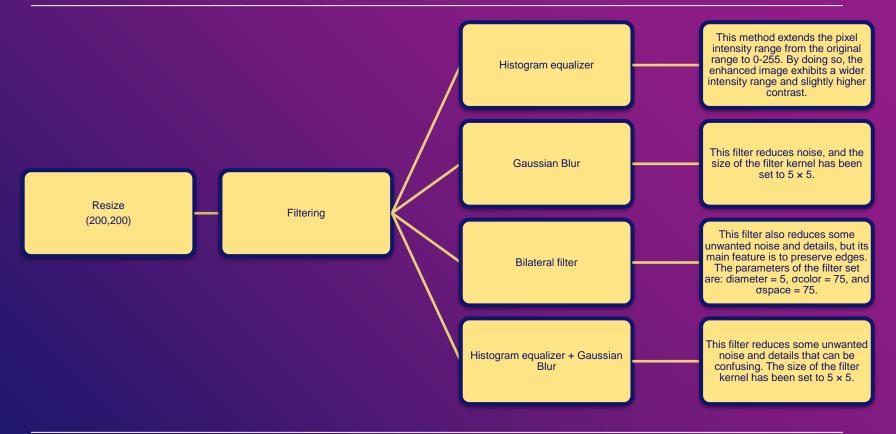






PREPROCESSING DATASET

DATA SCIENCE



RESIZING AND FILTERING

Immagine Resized

Histogram equalizer

Gaussian Blur

Bilateral Filter

Histogram equalizer + Gaussian Blur









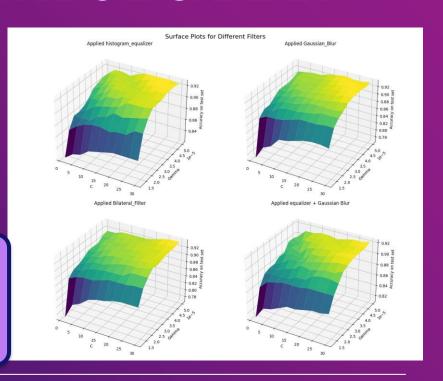


STIMA DEI PARAMETRI C E GAMMA

C beetween 1 and 30

Gamma beetween 1e-05 e 2.5e-05

The model's accuracy was evaluated on the test set for each type of filter.









Accuracy - Precision - Recall - F1- Score



PERFORMANCE MEASURES

Accuracy

 Accuracy represents the percentage of correct predictions compared to the total predictions.

Precision

 Precision indicates the percentage of correct positive class predictions compared to the total positive class predictions.

Recall

 The percentage of correct positive class predictions compared to the total positive cases.

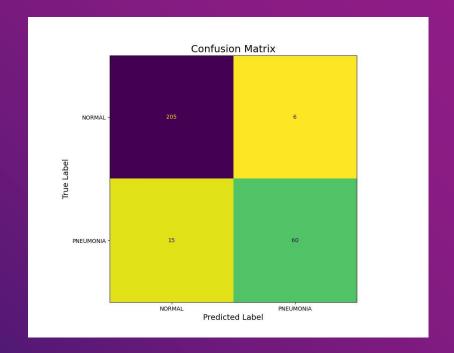
F1-Score

The harmonic mean of Precision and Recall

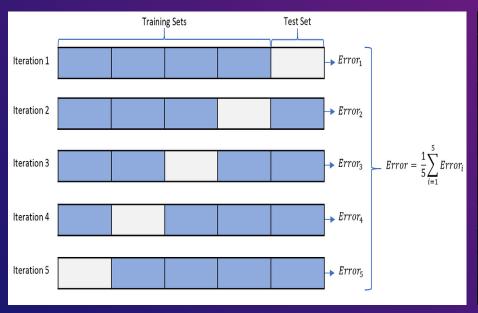
RESULTS

Results of the model with:

- Bilateral filter
- C = 30
- Gamma = 4.58e-05
- Accuracy = 0.93
- Precision = 0.91
- Recall = 0.8
- F1 score = 0.85



10 FOLD CROSS VALIDATION RESULTS



	fit_time	score_time	test_accuracy	test_precision	test_recall	test_f1
1 fold	18.882835	3.707422	0.923077	0.909091	0.789474	0.845070
2 fold	18.327481	4.841672	0.965035	1.000000	0.868421	0.929577
3 fold	18.717432	3.982299	0.944056	0.941176	0.842105	0.888889
4 fold	16.028239	3.645625	0.958042	0.970588	0.868421	0.916667
5 fold	16.654617	3.758519	0.937063	0.916667	0.846154	0.880000
6 fold	17.278660	3.559622	0.923077	0.868421	0.846154	0.857143
7 fold	17.323133	3.729944	0.958042	0.971429	0.871795	0.918919
8 fold	16.587952	3.731243	0.916084	0.885714	0.794872	0.837838
9 fold	16.173955	3.772663	0.902098	0.820513	0.820513	0.820513
10 fold	15.217180	3.516932	0.839161	0.666667	0.820513	0.735632
Mean results	17.119148	3.824594	0.926573	0.895027	0.836842	0.863025





















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