

Fig A. Top: Marker expression per cell measured using the images (top row) and the FR maps (middle row) overlaid on the tSNE plot for rest of the immune and tumor markers. The bottom row demonstrate correlation between marker expression per cell from raw images (x-axis) and FR maps (y-axis). The strength and direction of these correlations are quantified using Spearman's rank correlation coefficient. Left: Cells are sorted by cell types identified by our clustering (y-axis) against marker expression (x-axis). Expression values for each marker are measured from the FR maps. Stacked bar plot shows the abundance of each cell type in the dataset. Right: Cell-cell comparison between the cell type identified by the TNBC study versus our framework (left panel). Numbers in table cells indicate the percentage of cells in the dataset where columns and rows, respectively, compare their identified types by the baseline and our framework.



Fig B. Quantifying the correlation between the raw image pixel intensity and FR maps for marker-positive cells. Correlation plots illustrating marker expression per cell from raw images (x-axis) against FR maps (y-axis) are presented in rows 1 and 3. Specifically, these plots focus on cells where the average FR map values per cell exceed a selected threshold value. To rationalize the chosen threshold values (indicated by red lines), histograms displaying average values per cell measured from FR maps are included, delineating positive cells for a given marker from the negative ones. We note that the mapping from pixel values in the raw image to the FR map is influenced not only by pixel intensity but also by the spatial information of surrounding pixels. Consequently, positive signals may yield large values in the FR map; however, as these values increase in the raw image, the values level off in the FR map. This characteristic does not present any issues, as our framework is not designed to assess the level of expression for functional markers, but rather to determine whether a cell is positive or negative for a given marker.



Fig C. Cell types clustered by marker expression. Expression values for each marker are measured from the raw image (left) and the FR maps (right).

| Table A. Classification features extracted for the breast cancer and the ovarian can | er datasets. |
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|--|--------------|

| Feature | Number of extracted | Notes |
|----------------------------|-----------------------------|---|
| Gaussian | 5 | Performs 5 convolutions of Gaussian kernels with the 5 variations of σ and |
| blur | $(\sigma = 1, 2, 4, 8, 16)$ | generates 5 features for each image. |
| Sobel filter | 5 | Calculates an approximate of the gradient of the image intensity at each pixel for each image after applying 5 variations of Gaussian blurs; generates 5 features for each image. |
| Difference of Gaussians | 10 | Calculates two Gaussian blur images from the original image and subtracts one from the other. Thus, with 5 variations of Gaussian blur, 10 features are generated for each image. |
| Mean | 5 | Mean is calculated from the pixels within a radius of σ pixels from the target pixel and the target pixel is set to that mean value. With 5 variations of Gaussian blur, 5 features are generated for each image. |
| Median | 5 | Median is calculated from the pixels within a radius of σ pixels from the target pixel and the target pixel is set to that median value. With 5 variations of Gaussian blur, 5 features are generated for each image. |
| Entropy | 20 | Within radius σ around each pixel, generates the histogram of that circle using n = 32, 64, 128, 256 as the number of bins and calculates the entropy as $\Sigma - p*\log_2(p)$, where p is the probability of each collection in the histogram. With 5 variations of Gaussian blurs adds 20 features for each image. |

Table B. Classification features from Table A in descending order of importance for CD20 marker from breast cancer dataset.

| Features | Information gain ratio score |
|-----------------------------------|------------------------------|
| Original image | 0.3192 |
| Gaussian blur 2.0 | 0.8789 |
| Gaussian blur 4.0 | 0.8744 |
| Entropy 2 64 | 0.866 |
| Entropy 2 256 | 0.8628 |
| Entropy 2 128 | 0.8625 |
| Difference of gaussians 2.0.1.0 | 0.8612 |
| Mean 2.0 | 0.8607 |
| Gaussian blur 10 | 0.8547 |
| Difference of gaussians 4.0.1.0 | 0.8373 |
| Mean 4.0 | 0.8356 |
| Entropy 1 256 | 0.8328 |
| Entropy 1 128 | 0.8328 |
| Mean 10 | 0.8294 |
| Entropy 1 64 | 0.8251 |
| Entropy 4 256 | 0.8251 |
| Entropy 4 128 | 0.8248 |
| Sobel filter 1.0 | 0.8240 |
| Entropy 4, 64 | 0.8242 |
| Gaussian hlur 80 | 0.7958 |
| Difference of gaussians 16.0.8.0 | 0.7953 |
| Sobel filter 2.0 | 0.7555 |
| Difference of gaussians 8.0.1.0 | 0.7739 |
| Difference of gaussians 16.0.4.0 | 0.7333 |
| Difference of gaussians 10.0 4.0 | 0.7483 |
| Sobol filter 0.0 | 0.7308 |
| Difference of gaussians 8.0.4.0 | 0.7233 |
| Mean 8.0 | 0.7043 |
| Entropy 8 256 | 0.6931 |
| Entropy 8 128 | 0.6928 |
| Entropy 8 64 | 0.6894 |
| Difference of gaussians 16.0.2.0 | 0.6782 |
| Sobel filter 4.0 | 0.6776 |
| Difference of gaussians 8.0.2.0 | 0.6709 |
| Entropy 2, 32 | 0.6708 |
| Gaussian blur 16.0 | 0.6663 |
| Entropy 4, 32 | 0.6334 |
| Difference of gaussians 16.0, 1.0 | 0.6334 |
| Entropy 1 32 | 0.5938 |
| Entropy_1_32 | 0.5350 |
| Entropy_16_64 | 0.5726 |
| Entropy_16_04 | 0.5720 |
| Sobel filter 8.0 | 0.574 |
| Mean 16.0 | 0.5548 |
| Entropy 8 32 | 0.5352 |
| Entropy_6_52 | 0.3201 |
| Sobel filter 16.0 | 0.4312 |
| Median 10 | 0.3233 |
| Median 2.0 | 0.3140 |
| Median 4.0 | 0.295 |
| Median 8.0 | 0.0309 |
| Median 16.0 | 0 |
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Fig D. The figure displays the top 5 features utilized for pixel classification of images from the CD20 channel from the breast cancer dataset.