Automated Mitosis Detection Using Bag-of-Visual-Words and Classical Image Processing Techniques

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***Abstract*—This paper presents a classical computer vision pipeline to detect mitosis instances in breast cancer histopathological images. The proposed system combines background segmentation using local intensity analysis, Bag-of-Visual-Words (BoVW) with local descriptors, and classification via a Random Forest. The model is evaluated using F1 score and pixel-wise Intersection over Union (IoU), yielding competitive performance across validation and test sets.**

I. Introduction

Breast cancer severity is often assessed by counting mitotic figures in biopsy samples. Manual counting is labor-intensive and prone to observer variability. This work aims to automate mitosis detection using classical image analysis techniques, enabling robust, low-resource solutions for medical diagnostics.

II. Dataset

Microscopy images from five patients (A00–A04) were used, with A00 used for testing, A02 for validation, and A01, A03, A04 for training. Each image is 2084×2084 pixels and is accompanied by a CSV file containing mitosis coordinates.

III. Methodology

A. Visualization of Mitosis Points

To begin, mitosis locations from the CSV files were visualized on their respective images. Annotated mitotic figures were marked in red on the original images using OpenCV. Visualization aided in understanding their typical appearance and context.

B. Background Segmentation

To isolate nuclei and other relevant structures from the histological background, we developed a function `preprocess_and_segment`. This method enhances regions that are significantly darker than their local surroundings—an observation consistent with the appearance of mitotic figures under the microscope.

The segmentation process consists of the following steps:

1) **Grayscale Conversion and Denoising:** The original RGB image is converted to grayscale to simplify intensity analysis. A Gaussian blur with a 5×5 kernel is applied to suppress high-frequency noise while preserving structural features.
2) **Local Mean Filtering:** A 3×3 averaging filter is used to compute the local mean intensity for each pixel. This step helps determine the contextual brightness around each pixel and forms the basis for adaptive thresholding.
3) **Intensity-Based Masking:** Two binary masks are generated by comparing each pixel's intensity to its local mean:
   - **Darker Regions:** Pixels that are significantly darker than the local mean (by a defined threshold) are marked.
   - **Brighter Regions:** Pixels significantly brighter than the local mean are also identified to exclude false positives from high-intensity artifacts.

   The brighter region mask is subtracted from the darker region mask to emphasize the truly darker regions, and the result is clipped to maintain valid binary output.
4) **Morphological Post-Processing:** To refine the segmentation and remove noise, several morphological operations are applied:
   - **Opening (3 iterations):** Eliminates small noise particles via erosion followed by dilation.
   - **Closing (2 iterations):** Fills small gaps in segmented regions via dilation followed by erosion.
   - **Dilation (6 iterations):** Further enlarges the detected regions to ensure coverage of entire nuclei.

   Finally, the binary mask is thresholded again to ensure consistency and clarity in the resulting segmentation.

This method relies on local contrast and morphological reasoning, making it robust against global lighting variations and histological staining differences.

The segmentation threshold was empirically tuned using ground truth mitosis annotations, evaluated with mean pixel-wise Intersection over Union (IoU). Through iteration, a threshold value of 0.1 yielded the most effective trade-off between true positive coverage and noise suppression.

C. Feature Extraction

To represent each segmented cell as a fixed-length numerical vector suitable for classification, a combination of Bag-of-Visual-Words (BoVW) and handcrafted features was employed. This hybrid feature design captures both the visual texture and geometric properties of each region.

1) Bag-of-Visual-Words (BoVW) Dictionary Construction: The BoVW dictionary was constructed using Scale-Invariant Feature Transform (SIFT) descriptors extracted from all training images. The steps are as follows:

1) All SIFT descriptors from the training set were aggregated.
2) K-Means clustering was applied to group descriptors into 100 clusters, each representing a distinct "visual word."
3) Each cell was later described using a histogram of visual word occurrences, indicating the frequency of appearance of each cluster.

This process produced a 100-dimensional vector per cell, encoding keypoint-based visual structure in a scale- and rotation-invariant manner.

2) Region-Level Feature Extraction: After background segmentation, connected components were identified, each representing a candidate cell. For each component, the following features were computed:

- **Texture Features:**
  - *Local Binary Patterns (LBP):* Encodes local texture by thresholding neighboring pixels.
  - *Gray-Level Co-occurrence Matrix (GLCM):* Captures statistical properties including contrast, energy, homogeneity, and correlation.
- **Shape Features:**
  - *Aspect Ratio:* Width-to-height ratio of the bounding box.
  - *Solidity:* Ratio of the area to the bounding box area.
  - *Perimeter and Circularity:* Derived using contour detection; circularity is defined as $\frac{4\pi \times \text{Area}}{\text{Perimeter}^2}$.
- **Color Features:**
  - *Mean and Standard Deviation in HSV:* Extracted from the cell region in HSV color space to capture color tone and intensity variations.
- **BoVW Histogram:**
  - A normalized histogram over the 100 visual words was computed using SIFT descriptors within the cell region.

3) Label Assignment and Output: For training and validation datasets, mitosis labels were automatically assigned using a bounding-box level Intersection-over-Union (IoU) comparison with the ground truth mitosis coordinates. A mitosis was considered detected if its IoU with a connected component exceeded a pre-defined threshold.

Each feature vector was stored along with its image reference, centroid position, and binary label (mitotic or non-mitotic), producing a labeled feature dataset saved as a CSV file for downstream classification.

D. Classification

For distinguishing mitotic from non-mitotic cells, we employed a Random Forest classifier, which is robust to high-dimensional feature spaces and capable of handling class imbalances. The final model configuration was defined as follows:

```
RandomForestClassifier(
    n_estimators=200,
    max_depth=20,
    min_samples_leaf=3,
    min_samples_split=4,
    class_weight="balanced"
)
```

The classification task was challenging due to a significant class imbalance (2,228 non-mitotic vs. 161 mitotic examples). The Synthetic Minority Over-sampling Technique (SMOTE) was tested but discarded due to increased false positives. Instead, hyperparameters—particularly `class_weight='balanced'`—were tuned to mitigate bias toward the majority class, enhancing sensitivity for mitotic detection. Hyperparameter optimization was driven primarily by the validation F1 score and pixel-wise Intersection-over-Union (IoU).

IV. Results

A. Validation Results

- **F1 Score:** 0.278

Class	Precision	Recall	F1-score
Non-Mitotic	0.99	1.00	0.99
Mitotic	0.42	0.21	0.28

TABLE I
VALIDATION CLASSIFICATION REPORT

B. Pixel-wise IoU Results

- **A00_v2 (Test Set):** 0.2627
- **A02_v2 (Validation Set):** 0.1089

V. Conclusion

The developed pipeline demonstrates the feasibility of automated mitosis detection in histopathological images using classical image processing and a BoVW-based classification approach. Despite the significant class imbalance and inherent complexity of mitosis identification, the method achieved moderate success in detecting mitotic events, with an F1 score of 0.278 and mean pixel-wise IoU of 0.2627 on the test set. Future improvements may include enhancing mitotic recall by refining segmentation methods, integrating advanced feature extraction, or employing deep learning techniques, which could yield more accurate and robust predictions.

Keywords—Mitosis Detection, Breast Cancer, BoVW, Image Segmentation, Random Forest