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Pixel Intensity in Mammography: A Factor of Error in Breast Cancer Detection

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Abstract. Doctors may find it challenging to identify breast cancer through mammography, but image processing can assist. Tumors and macrocalcifications are typically detectable using pixel intensity analysis. The issue with this approach is that its high false positive rate causes diagnostic errors and needless biopsies.
In this work, we investigate the dependability of mammography analysis techniques based on pixel intensity. Otsu thresholding, K-means clustering, and "contrast-limited adaptive histogram equalization (CLAHE)" are examples of segmentation and classification techniques that frequently have flaws, according to research in the literature. These errors are caused by variations in breast tissue, noise sensitivity, and imaging artifacts.
Although hybrid methods (like CNNs, SVMs, and CANs) can reduce false positives by up to 30%, they are challenging to apply for small lesions. Based on previous research, we discovered that tumors cannot be reliably classified using only pixel intensity. Combining morphological, textual, and contextual parameters is crucial for improving breast cancer detection ans reducing false positives.

Keywords: Medical imaging, Mammography, Pixel intensity, False positives.

1 Introduction

Worldwide women are still at risk from breast cancer. If you wish to survive and receive treatment, you must detect this illness as soon as possible. Mammography is the best method for screening breast cancer because it is non-invasive and good at identifying suspicious areas. These images still have issues with diagnostic accuracy and are challenging to read.
The most frequent problem with interpreting mammograms is false positives. Misdiagnosing benign lesions such as cancer results in needless biopsies, anxiety in patients, and wasteful use of medical funds. Numerous biological and technical factors, including image noise, breast tissue density, and algorithm limitations, are involved.
Artificial Intelligence (AI) and image processing classify anomalies using feature vector parameters, which facilitate diagnosis. For instance, tumors and microcalcifications within a tumor can be identified using the intensity of the pixels. Using intensity alone is

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insufficient. It is not suitable for primary detection because it is sensitive to noise and prone to false alarms.
This study is intended to evaluate mammography pixel intensity, so we will examine it and look for a different strategy that might lower false positives.

2 Medical Imaging Feature Vectors

Feature vectors are similar to electronic fingerprints in medical imaging, such as mammography, by turning an image's visual characteristics into data points, so machines are able to analyze it, and understanding these characteristics is necessary to classify anomalies, such as benign or malignant tumors.
You can interpret these features as follows:

- **Tumor shape:** We analyze the geometry of a mass to see if it is "normal" or suspicious:
  - **Technical aspects:** It is possible to calculate the centers of mass, orientations, and sizes using geometric moments (lower-order moments) and to detect symmetry using geometric moments (higher-order moments). The frequencies in a shape can be analyzed using the Fourier function.
  - **Significance:** Circular masses are generally benign (such as cysts). On the other hand, irregular shapes or multilobulated masses are indicative of malignancy.
- **Texture:** An image surface's texture or complexity is measured by texture analysis:
  - **Technical aspects:** We measure the Entropy (Disorder) and Contrast (Pixel-by-pixel differences in intensity). Homogeneity also determines how uniform the texture is.
  - **Significance:** Most malignant tumors are chaotic in nature. In general, they are heterogeneous, with a high entropy and sharp contrast variation. Most benign masses are smooth and homogeneous in texture.
- **Pixel Intensity:** The tumor's brightness is mapped against its background luminosity.
  - **Technical aspects:** The Intensity Histogram displays the distribution of gray levels within an image.
  - **Significance:** Malignant tumors may appear "hyperdense" (brighter) or "hypodense" (darker) based on the scan's contrast.
- **Location:** This identifies the problem.
  - **Technical aspects:** The exact location of the suspected area is recorded.
  - **Significance:** Diagnostics and treatment planning are influenced by location. For example, according to statistics, the upper outer quadrant of the breast is more likely to be affected by cancer.

- **Tumor border:** The characteristics of the tumor border are highly predictive.
    - **Technical aspects:** To calculate how complex the border is, we use Fractal Dimensions, and to determine edge sharpness, we use Contour Analysis.

    - **Significance:** The edges of benign tumors are typically sharp and clean, then malignant tumors frequently have borders that are sharp, hazy, or extremely complicated.
- **Density**
    - **Technical aspects:** This involves comparing the mass density with the surrounding tissue.

    - **Significance**: In breast cancer, tissue that appears significantly denser than the rest of the breast is often an indicator of malignancy.

- **Symmetry**
    - **Technical aspects:** The breast's natural structure is used to calculate how symmetrical the mass is.

    - **Significance:** Cancer does not follow nature's symmetry. A breast that's out of symmetry is usually a sign to watch for.

These features are used by many machine learning models, such as "*Convolutional Neural Networks (CNNs)",* they aid AI in differentiating between malignant and benign cysts, so the inaccuracy of these features like pixel intensities, which are very vulnerable to "noise" in images and human error, is one of the difficulties in this process.

3 The Pixel Intensity: A Key Indicator of Classification and Segmentation

Pixel intensity in mammograms reveals the distribution of grayscale tones throughout the picture, suspicious findings, such as tumors or microcalcifications, frequently contrast sharply. This disparity has been utilized in recent research to improve anomaly detection techniques:

3.1 The Limits of Pixel Intensity in Studies

Pixel intensity for medical image analysis has been examined in a number of studies, which have shown both its advantages and disadvantages.

- ***"Zepeda Fernández [1] :*** *A combination of pixel intensity, entropy, and fractal dimension is used to segment tumors and microcalcifications. The study defined suspect areas as ones that had an intensity three times that of normal tissue. Due to natural tissue variability and noise, false positives were moderate to high."*

- ***"Nithya[2]:*** *Utilized Artificial Neural Networks (ANN) to build a Computer-Assisted Diagnosis (CAD) system. There was a remarkable 98% accuracy in the system, indicating that intensity is a reliable indicator. However, the study* *noted that performance depends on the quality and diversity of training datasets."*

- ***"Shanmugavadivu[3] :*** *Otsu thresholding was applied to microcalcification segmentation. In the image, artifacts and noise caused high false-positive rates, but they enhanced contrast. Therefore, pixel intensity alone isn't robust enough to tell anomalous brightness variations from normal ones."*

- ***"Alshamrani[4] :*** *combined Histogram Intensity Windowing (HIW) and Convolutional Neural Networks (CNNs). While these sophisticated techniques were used to develop the model, it only achieved 62% accuracy on the mini-MIAS database, demonstrating that intensity-based methods often require extensive preprocessing."*

3.2 The Impact of Pixel Intensity on False Positives in New Studies

Further, we examined four studies for which pixel intensity is used specifically to reduce false positives.

- ***"Almalki [5] :*** *used K-means clustering combined with "Contrast Limited Adaptive Histogram Equalization (CLAHE)". Pixel intensity is used to cluster and segment suspicious areas without prior labeling, so this method is reasonably precise in segmenting suspicious areas. It can, however, generate false positives due to its sensitivity to image noise. This result could be significantly improved by integrating additional preprocessing steps to denoise the data."*

- ***"Li [6]:*** *characterized breast tissue textures using a hybrid CNN that includes multifractal analysis. For this model, pixel intensity is used to extract multifractal features. The strategy decreased false positives by 22% when compared to conventional techniques. Its primary drawback in terms of efficacy is the challenge of identifying tiny lesions."*

- *"NIHMS-1782722 [7]: To isolate discriminative information, a "CNN" is combined with "Gray-Level Co-occurrence Matrix (GLCM)" texture features. In order to capture the spatial relationships between pixels in this study, a GLCM matrix was computed using pixel density. False positives were decreased by 30% when SVMs and deep learning were combined. It can't process big datasets in real time because of its high cost, despite its effectiveness."*

- ***"Oza [8] :*** *The anomalies were detected using a combination of SVMs, CNNs, and "Generative Adversarial Networks (GANs)". In this deep learning model, pixels are used to differentiate normal tissues from pathological ones. The problem with CNNs is that they have average false positive rates, but they have trouble detecting minute anomalies. These small structures are often misclassified, so they need to be refined."*

3.3 False Positives and Comparison of Methods

False positives are still a problem in mammography analysis, frequently leading to needless biopsies and upsetting patients. We compare the techniques examined in the table below according to their efficacy and false positive rates to demonstrate how various strategies address this issue.

Table 1. Comparison of Methods and Impact on False Positives

Study	Method Used	Classification Model	FP Reduction	Critique of FPs
Zepeda Fernández [1]	Fractal Analysis + Pixel Intensity	Supervised Learning	Moderate	Good segmentation but requires precise calibration.
Nithya [2]	Average Pixel Intensity + ANN	Neural Networks	Reduced	High accuracy (98%) but highly dependent on dataset quality.
Shanmugavadivu [3]	Otsu Thresholding + Histogram Bins	Supervised Learning	High	Effective segmentation but generates many FPs due to noise.
Alshamrani [4]	HIW + CLAHE + CNN	CNN	Reduced	FP reduction but requires advanced preprocessing and optimization.
Almalki [5]	CLAHE + K-means Segmentation	Unsupervised Learning	Moderate FPs	Sensitive to noise; requires additional preprocessing.
Li [6]	Multifractal Analysis + CNN	Hybrid CNN	22% Reduction	Struggles with small lesions, limiting overall effectiveness.
NIHMS-1782722 [7]	GLCM Texture Fusion + CNN	SVM + Deep Learning	30% Reduction	Highly effective but computationally expensive, limiting real-time applications.

3.4 Reasons for Pixel Intensity's Failure in Changing Environments

False positives (FPs) in pixel intensity mammography can occur for a number of reasons, so the primary cause is that biological tissue is much more complicated than it first appears.

1. **Breast tissue variation:** Every breast is different in terms of density and texture. This variability can be misinterpreted as an anomaly, leading to FPs.

2. **Noise detection:** Mammography images can be affected by noise, lighting, and artifacts, because pixel intensity is very sensitive to these factors, false positives often occur.

3. **Small lesion detection:** Pixels that look like small tumors or microcalcifications can also appear in normal tissue, because they are hard to tell apart, they often lead to more false positives.

4. **Methods lack robustness:** A technique such as Otsu thresholding or K-means segmentation does not consider the context of the images.

4 Challenges and Future Prospects

Mammography pixel intensity has significantly improved over time, it is still a challenging area to control and obtain totally accurate results from:

1. **Reduce noise:** False positives are caused by excessive noise, examples of sophisticated filtering methods that can significantly enhance image quality and diagnostic accuracy are deep learning models and adaptive filters.

2. **Calibrating models:** Hybrid methods like fractal analysis and neural networks require fine-tuning segmentation errors. Adaptive algorithms could account for individual breast tissue variations.

3. **Contrast learning:** Utilizing subtle differences in pixel intensity can help differentiate between normal and pathological tissues using contrastive learning techniques.

4. **Multi-datasets:** Model performance depends heavily on data quality and diversity. An international collaboration could help create a bigger, more representative database.

5. **Clinical Integration:** Systems based on pixel intensity must integrate seamlessly into clinical workflows, with intuitive user interfaces and fast processing.

5 Conclusion

It is possible to detect and classify breast anomalies using pixel intensities, if sophisticated image processing and machine learning are integrated. Neural networks and fractal analysis can be combined to improve diagnostic accuracy and lower false positive rates. The future will be about researching image preprocessing, adaptive algorithms, and a variety of databases, these technological benefits will have to be converted into practical patient benefits by the researchers, engineers, and the medical community.

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