Automatic Detection of Simulated Motion Blur in Digital Mammograms

Nada Kamona and Murray Loew

The Medical Imaging and Image Analysis Laboratory, Department of Biomedical Engineering

The George Washington University, Washington, DC

nkamona@gwmail.gwu.edu

School of Engineering & Applied Science, THE GEORGE WASHINGTON UNIVERSITY

GW Biomedical Engineering

INTRODUCTION

- **Blur** is lack of sharpness and degradation of an image due to motion and/or poor focus.
- **Motion blur** is a known phenomenon in full-field digital mammography that arises during image acquisition [5].
- Blur has been reported to reduce lesion detection performance and mask small microcalcifications [1], resulting in failure to detect smaller abnormalities until they reach more advanced stages [4].

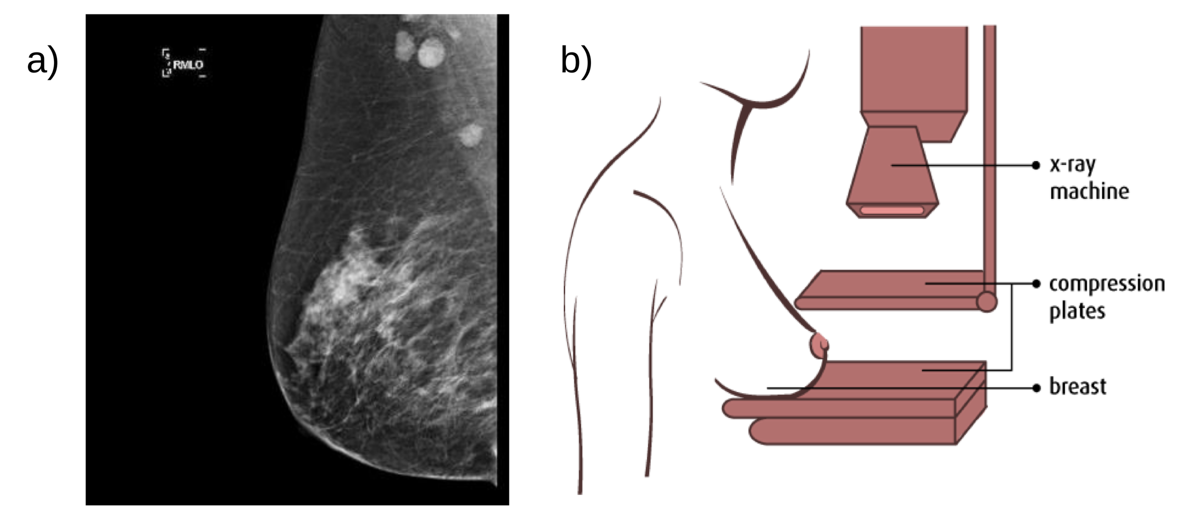


Fig 1. a) Blurred mammogram containing a microcalcification in the posterior of the lower breast that cannot be detected[4]. b) Schematic diagram showing how mammography is done.

- It is estimated that 20% of screening mammograms show elements of blur [4] [5].
- Motion blur can occur due to patient movement and paddle motion during the clamping phase, which might cause movements of up to 1.5 mm in the vertical plane [5].
- **As far as we know, no work has been done to automatically detect motion blur in mammograms other than Hill et al [3].**

OBJECTIVES

We propose using machine-learning algorithms to detect motion blur in mammograms automatically, which could be used as a support for the clinical decision-making process during the mammography exam. The goals of this project are to:

1. Simulate blur in mammograms to mimic the effect of blurring produced during image acquisition.
2. Investigate the ability of various classifiers to detect simulated blur in digital mammograms

References

[1] Abdullah, A. K., Kelly, J., Thompson, J. D., Mercer, C. E., Aspin, R., & Hogg, P. (2017, 07). The impact of simulated motion blur on lesion detection performance in full-field digital mammography. *The British Journal of Radiology, 90*(1075), 20160871. doi:10.1259/bjr.20160871

[2] Boracchi, G., & Foi, A. (2012). Modeling the performance of image restoration from motion blur. IEEE Trans. Image Processing, 21(8), 3502-3517.

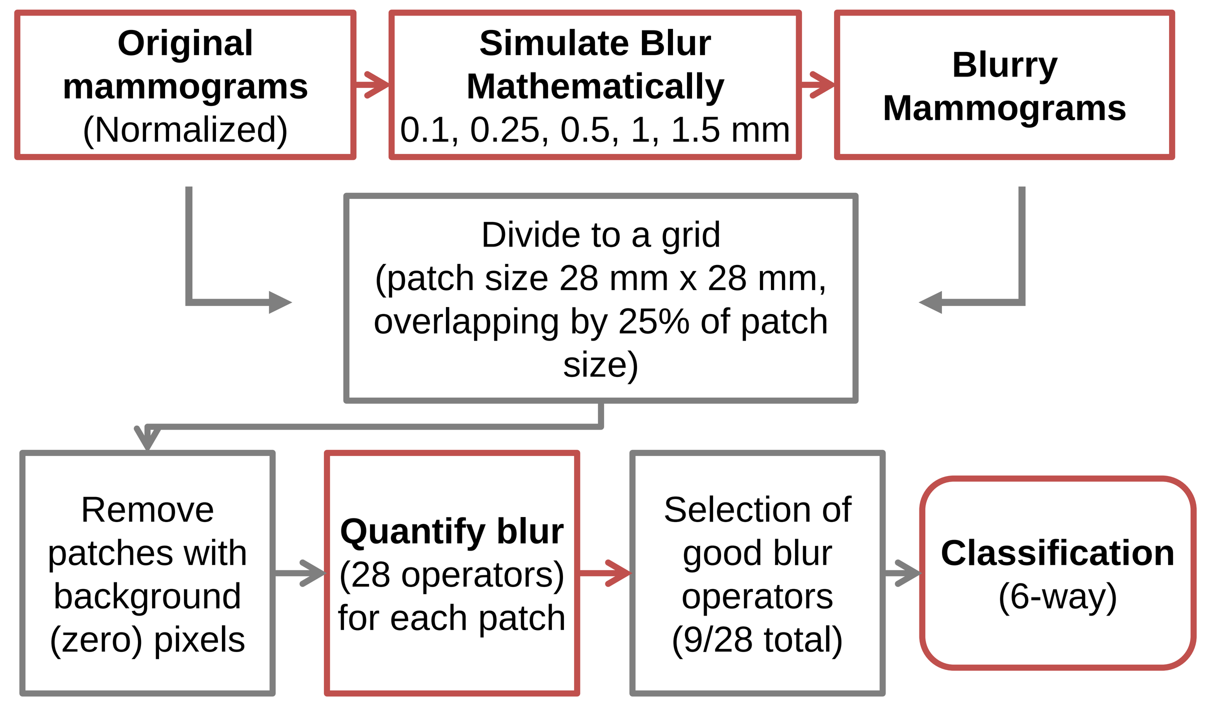
[3] Hill, M. L., Whelehan, P., Vinnicombe, S. J., Evans, A., Highnam, R. P., Tromans, C. E., . . . Brady, J. M. (2018, 07). Development of an automated detection algorithm for patient motion blur in digital mammograms. *14th International Workshop on Breast Imaging (IWBI 2018)*. doi:10.1117/12.2318225

[4] Hogg, P., Szczepura, K., Kelly, J., & Taylor, M. (2012, 02). Blurred digital mammography images. *Radiography, 18*(1), 55-56. doi:10.1016/j.radi.2011.11.008

[5] Ma, W. K., Aspin, R., Kelly, J., Millington, S., & Hogg, P. (2015, 08). What is the minimum amount of simulated breast movement required for visual detection of blurring? An exploratory investigation. *The British Journal of Radiology, 88*(1052), 20150126. doi:10.1259/bjr.20150126

METHODS

Study Design



Random-Motion Blur Model

Displace an individual pixel by a random vector (within the range of the blur effect), and the pixel contribution to the overall image is then sampled on a regular pixel grid using subpixel linear interpolation [2][5].

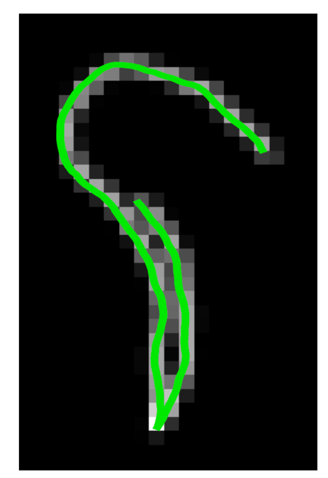


Fig 2. The trajectory (bold green) is sampled to create the blur point-spread function (PSF) mask [2].

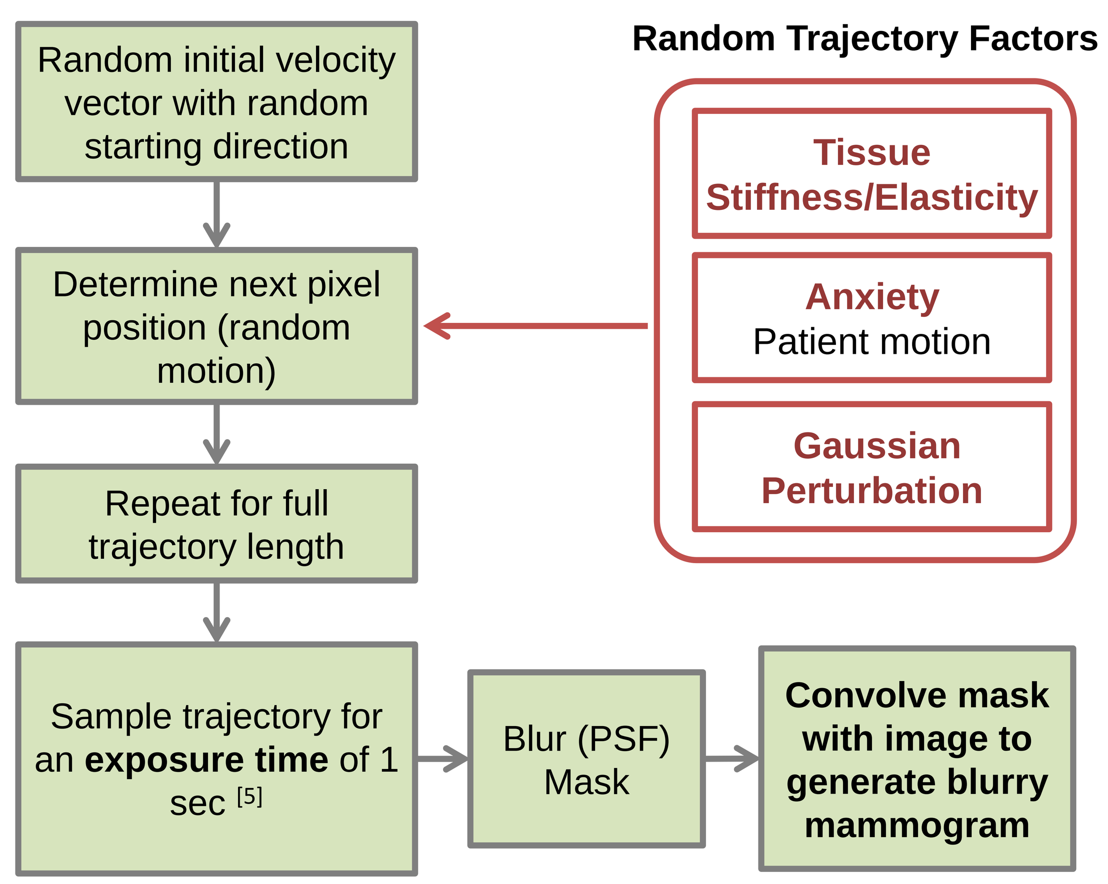


Fig 3. Simplified flowchart of motion blur trajectory and blur (PSF) mask generation [3].

Blur Measure Operators

A set of 9 operators measure the amount of blur at each pixel and in its local neighborhood. Examples:

Gaussian Derivative

$$M_{GD}(x,y) = \sum_{(i,j)\in\Omega(x,y)} \left((I \otimes G_x(i,j))^2 + (I \otimes G_y(i,j))^2 \right)$$

Energy of Laplacian

$$M_{EL}(x,y) = \sum_{(i,j)\in\Omega(x,y)} \Delta I(i,j)^2$$

Results

Blur magnitudes of 0.1, 0.25, 0.5, 1.0 and 1.5 mm of tissue motion were simulated on 244 Mammograms (*INbreast database*).

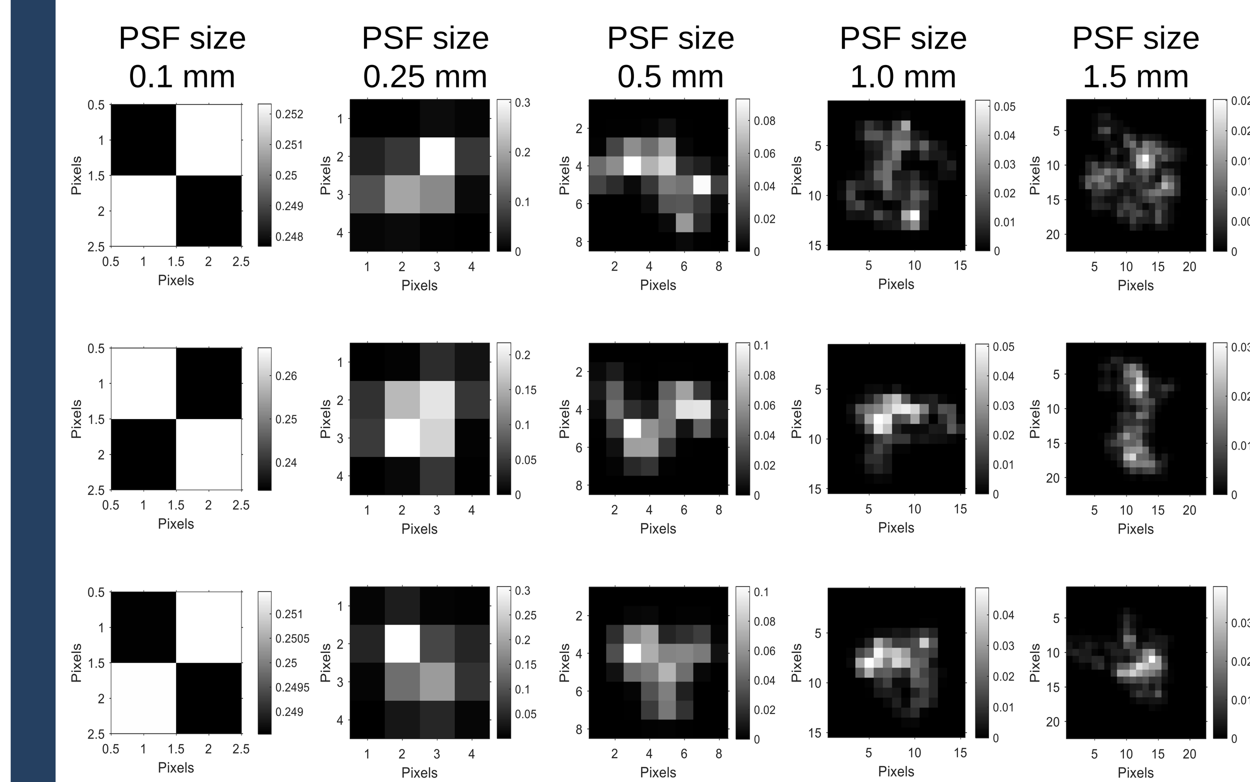


Fig 4. Examples of generated blur masks (point spread functions, [PSFs]), using the random trajectories approach, at five levels of blur. The pixel resolution is 70 microns for all masks. ***Blur mask size determines maximum amount of breast movement***.

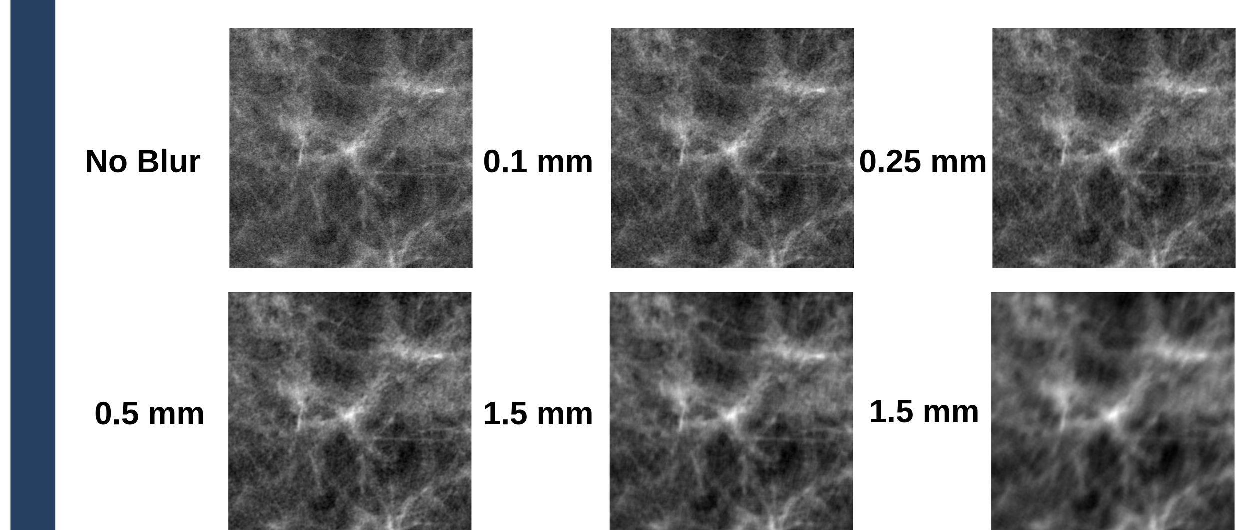


Fig 5. Mammogram patches (28 x 28 mm) with 5 levels of simulated blur.

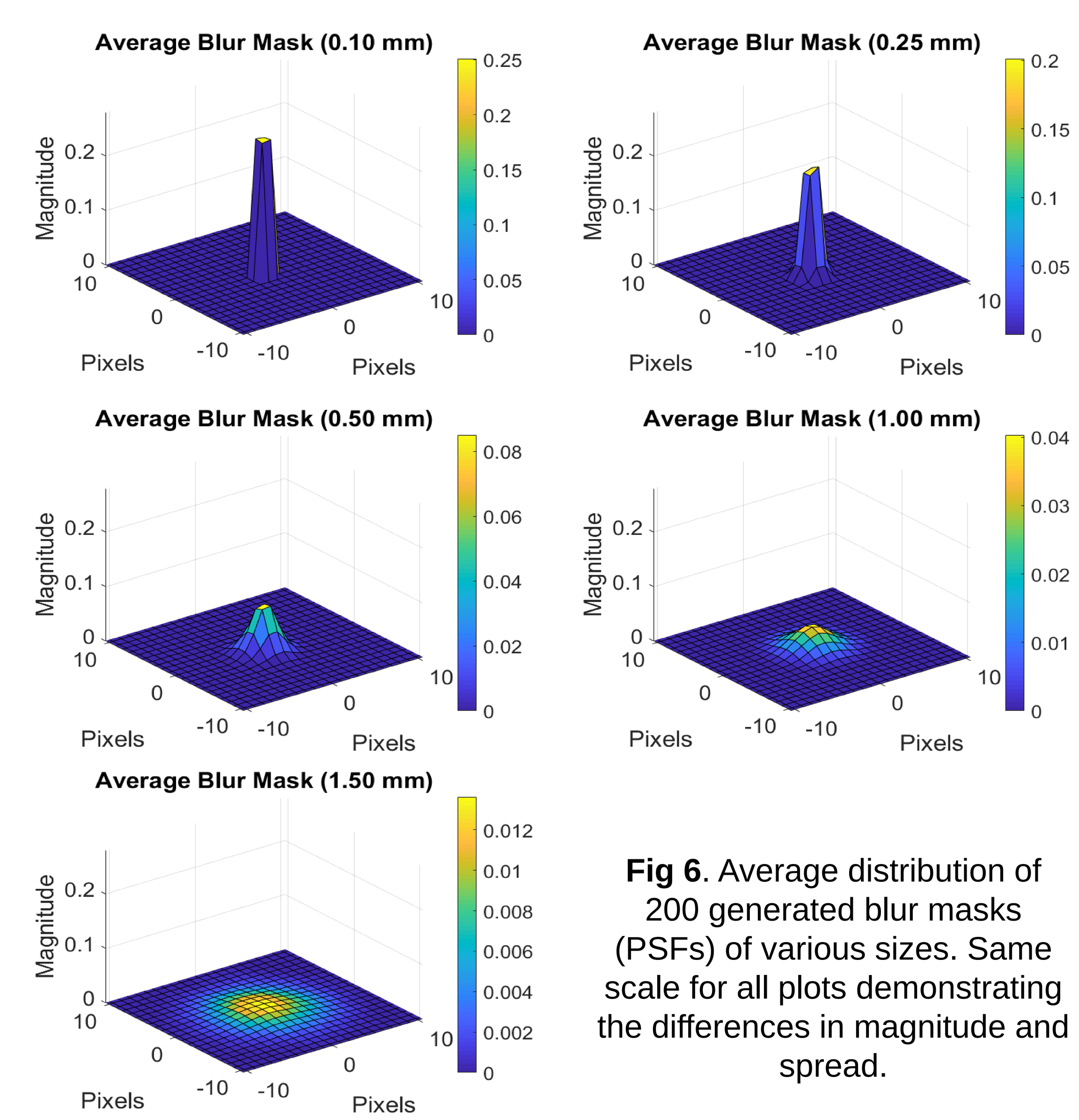


Fig 6. Average distribution of 200 generated blur masks (PSFs) of various sizes. Same scale for all plots demonstrating the differences in magnitude and spread.

Classification:

Patches divided into 70% training, 30% testing, 8745 and 3748 patches per class respectively.

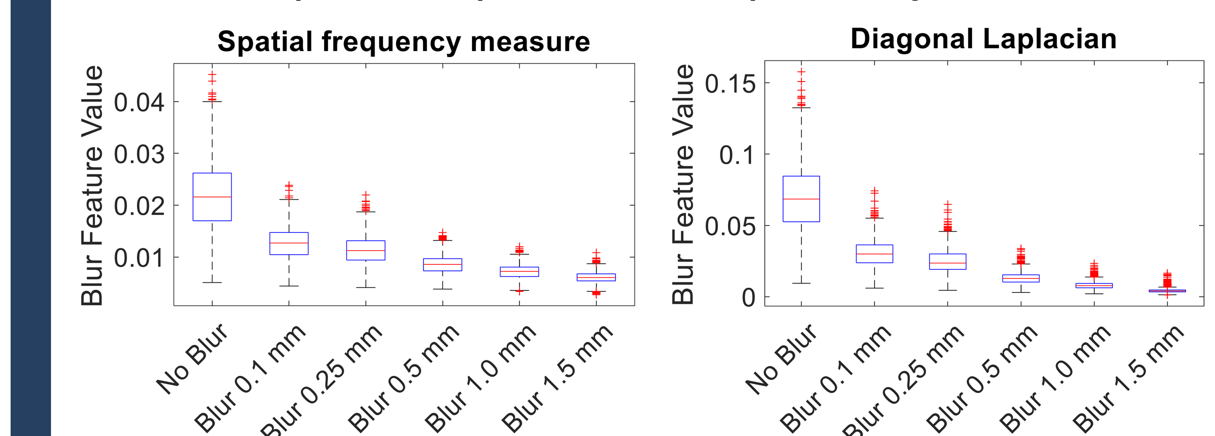


Fig 7. Blur Quantification measurements for mammograms without blur and mammograms with blur at five levels of blur severity using blur measure operators *Spatial frequency measure (left)* and *Diagonal Laplacian (right)* Each box plot contain measurements of 3748 mammogram patches.

Ensemble Bagged Trees

True class \ Predicted class	Blur 0.0 mm	Blur 0.1 mm	Blur 0.25 mm	Blur 0.50 mm	Blur 1.0 mm	Blur 1.5 mm	TPR	FNR
Blur 0.0 mm	8482	174	87	1	1		97.0%	3.0%
Blur 0.1 mm	1	7170	1399	174	1		82.0%	18.0%
Blur 0.25 mm	87	1749	6383	524	87		72.3%	27.7%
Blur 0.50 mm	1	1	437	7520	699	87	86.0%	14.0%
Blur 1.0 mm			1	612	7695	437	88.0%	12.0%
Blur 1.5 mm				1	262	8482	97.0%	3.0%
PPV	99.0%	78.8%	76.8%	85.1%	88.0%	94.2%		
FDR	1.0%	21.2%	23.2%	14.9%	12.0%	5.8%		

Fig 8. Confusion matrix of Ensemble Bagged Trees classifier for the training data

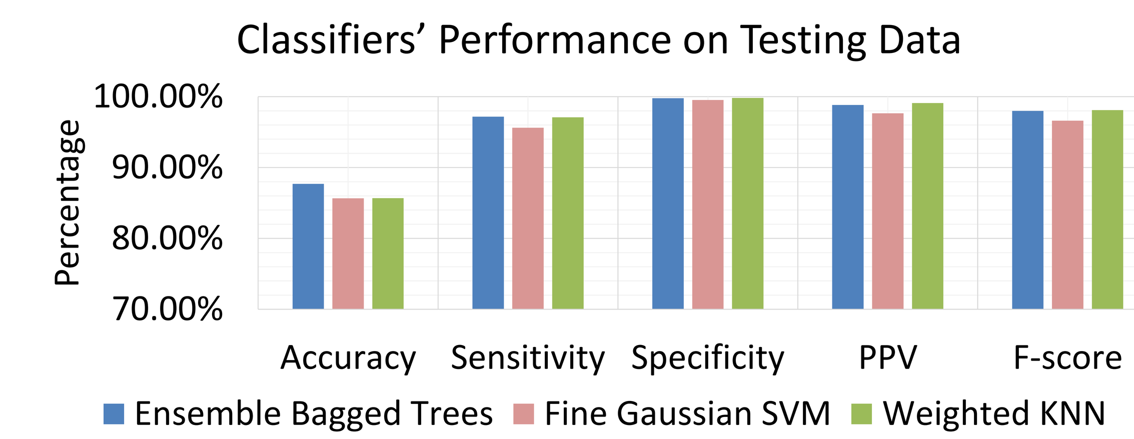


Fig 9. Average Classifiers' performance on testing data to classify unblurry mammograms and blurry mammograms at 5 levels of simulated blur.

CONCLUSION & FUTURE WORK

Although limited work has been done to quantify the effects of motion blur on radiologists' performance, there is evidence that motion blur could mask abnormalities and might not be detected visually by radiologists.

Automatic detection of blurry mammograms at the exam time has the potential to reduce return visits, false-negative decisions, and their implications in clinical practice.

Future Work:

- Validating the realism of the blur model.
- Simulate blur locally instead of globally.