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Original Article

CNNSVM-BF: A Robust Hybrid Feature-Based Approach for Blur Detection in Digital Breast Tomosynthesis Images

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Abstract - *Blur detection is an essential yet challenging task in digital image processing, particularly in medical imaging applications where image quality directly affects analysis reliability. In Digital Breast Tomosynthesis (DBT), motion artifacts and limited-angle acquisition frequently cause image blurring, degrading fine structural details, and complicating automated analysis. Blur detection in DBT is further challenged by the lack of prior blur knowledge and the visual similarity between blurred and sharp regions. This paper proposes a hybrid feature-based CNNSVM approach for detecting blur in DBT images by jointly utilizing automated image features extracted from a CNN with a BF (Laplacian-based Blur Factor). The BF, based on the variance of the Laplacian response, is applied to measure edge degradation and is used in conjunction with CNN-based features to enhance classification performance. The integrated feature set is characterized by a Support Vector Machine (SVM) model to identify blurred or non-blurred DBT images. Experimental evaluation using a large publicly available DBT dataset indicates that the hybrid scheme achieves an accuracy of 99.21% in blur detection. The model performed much better than CNN and CNNSVM models that rely only on image features. Furthermore, the hybrid design reduces complexity and maintains good performance at reduced training times. These findings indicate that the proposed framework provides a practical way to automatically blur detection in medical image processing tasks.*

Keywords - *Blur detection, Convolutional Neural Network, Digital Breast Tomosynthesis, Hybrid features, Laplacian operator.*

1. Introduction

Digital Breast Tomosynthesis (DBT), as an advanced imaging modality, especially for early breast cancer detection by providing quasi-three-dimensional visualisation of breast tissue with reconstructed thin-slice projections, has emerged [1]. By reducing tissue overlap compared to conventional mammography, DBT improves lesion conspicuity and structural differentiation. However, the limited angular acquisition and tube motion inherent in DBT often lead to blur artefacts, especially in the direction perpendicular to the direction of tube movement [2]. These artefacts can obscure fine anatomical structures, including microcalcifications, small deposits of calcium that could represent early malignancy.

Image interpretation and microcalcification detection may be affected by the quality of the acquired DBT series. The process relies heavily on the quality of the acquired DBT series that aids in image interpretation and microcalcification detection [3-5]. Due to their subtle morphology and small spatial extent, even minor blurring can degrade diagnostic reliability [6]. It is especially difficult to tell the tiny cancer cells from the large tumour microcalcifications in this way because of subtle blurring, and until they appear, the results are unnoticed or overlooked as they are much greater. Furthermore, DBT techniques produce several reconstruction slices per patient, adding more time and computing effort to their interpretations [7, 8]. Hence, robust image quality assessment mechanisms are crucial to avoid misclassification of diagnostically relevant slices or overlooking the diagnosis. Manual visual inspection is subjective, and there are no common quantitative measures for blurred content evaluation [9]. Therefore, image acquisition and image pre-processing are two of the fundamental parameters that ought to be taken into account by a comprehensive image quality evaluation process to maximize system performance and not hinder radiologist detection and interpretation work.

Blur detection in digital imaging is a challenging problem because blurred regions often exhibit visual characteristics similar to smooth but in-focus regions. In DBT images, this difficulty is amplified by complex anatomical textures and low-contrast structures. Traditional approaches rely on local sharpness metrics derived from gradients or frequency-domain information [10-12]. Due to the fact that blur results in a reduction of the presence of the high rate, edge decay is usually estimated either with gradients such as Gaussian or Laplacian operators. Deep learning methodologies, in particular Convolutional Neural Network (CNN), have shown great potential in automated feature extraction for visual recognition tasks [13]. Nevertheless, CNN-based blur detection models are heavily reliant on implicit feature learning and might need to be deep-trained to achieve strong discrimination. Such designs incur additional computational complexity and training cost that may curtail practical application in large-volume DBT screening protocols. In addition, image features alone might not fully describe physically meaningful blur characteristics, especially if the visual differences between blurred and non-blurred slices are minor. A study by Zhang et al. [14] made use of X-ray film data along with other clinical signs and symptoms to determine the patient's health status and management, and diagnose a disease. The 3 pieces of data used in this study, the X-ray film, clinical sign, and patient diagnosis, were defined as the image data, structured data, and the prediction results of a classifier, respectively. This observation emphasised that image data lacked specific and absolute information and that such data had to be integrated into structured data structures to confirm it.

Therefore, there is a research gap in developing a robust blur detection process that can combine physically interpretable blur descriptions with deep image representations and still remain computationally efficient. DBT applications especially benefit from addressing this gap, as high slice volume and fine-grained lesion structures demand both high performance and efficiency. To address these limitations, this paper introduces a hybrid CNNSVM framework that merges CNN-extracted image features with a Laplacian-based Blur Factor (BF) as structured numerical information. By integrating complementary feature representations, the proposed method improves blur discrimination while reducing dependency on deep network complexity.

The main contributions of this work are summarised as follows:

- Development of a hybrid feature framework combining CNN-based image embedding and Laplacian-based Blur Factor for DBT blur detection.
- Replacing the old SoftMax classifier with a Support Vector Machine (SVM) approach aims to enhance how the combined feature space is utilised for exploiting the dual feature space.
- Improved classification accuracy and lower computational cost when used with smaller training epochs than the image-only based methods.

The rest of this paper is organised as follows: Section 2 presents the literature review regarding blur detection approaches involving handcrafted and deep learning methods. Section 3 discusses the methodology of this study, while Section 4 describes the experimental results and analysis. Lastly, Section 5 concludes this study.

2. Related Work

DBT-based screening usually produces lots of reconstructed slices per patient. Because DBT systems do not allow a large number of angular acquisitions, out-of-plane artefacts are often observed in the direction of z. These artefacts are typically shown as blurred representations of in-plane structures in the direction of X-ray tube motion [15]. Consequently, there is a variation in image sharpness between the slices, which can potentially affect clinical reliability. As a result, no standard quantitative measurement is routinely applied for the severity of blurs in practice. Rather, image quality evaluation is mainly carried out in radiologists' qualitative judgment, which could lead to inter-observer heterogeneity. As a result, the development of objective and automated means for detecting blur in DBT images is a matter of great importance.

Blur detection is different from general recognition problems as it requires determining degradation characteristics rather than labels of semantically distinct objects. Difficulties of separating blurred areas and smooth yet in-focus areas, especially in complex anatomical textures, are the main ones. Unlike classification tasks that may tolerate multiple degradation types, such as noise or illumination variation, blur detection must specifically isolate blur-related features while remaining robust to content variability. While traditional feature extraction methods like Histogram of Oriented Gradients (HOG) or Speeded-Up Robust Features (SURF) have been used in earlier works, deep feature representations using Convolutional Neural Networks (CNNs) achieved an outstanding performance in many visual analysis tasks [16]. Although the present work integrates both structured and deep features, it is necessary first to examine the evolution and limitations of existing handcrafted and deep learning-based blur detection approaches.

2.1. Handcrafted Methods for Blur Detection

Handcrafted blur detection techniques have historically relied on manually designed descriptors derived from spatial gradients or frequency-domain analysis. Since blur reduces high-frequency content and weakens edge responses, many traditional methods estimate blur by measuring gradient magnitude, edge density, or spectral energy distribution [17-20] Blur detection generally operates on three related tasks: detection (identify whether blur exists), estimation (quantify blur strength), and classification (determine blur type) [17].

Blur detection is even more important with DBT imaging because of the high number of slices per patient and because of the small details of diagnostically relevant structures, including microcalcifications. The aim of handcrafted features is to quantify local detail variation; such variation is anticipated to be smaller in regions with blurred images than in sharp areas. Several gradient-based and frequency-based approaches have been proposed to exploit this property [18-21]. For example, Su et al. [22] incorporated gradient distribution patterns with singular value decomposition-based metrics to localise blurred areas. Moreover, a multiscale fusion process with sorted gradient magnitudes was developed to improve defocus blur map estimation. [20] While such handcrafted approaches are generally found to perform well in images with simple as well as well-ordered features, performance is limited in anatomically complex images. Such approaches will frequently have problems matching naturally smooth areas and truly blurred areas. Moreover, handcrafted descriptors lack semantic representation features, requiring fine-tuning of thresholds with potentially poor generalisation across datasets and acquisition cases. These limitations have led people to explore automated feature learning techniques which are sensitive to high-level abstractions.

2.2. Deep Learning Methods for Blur Detection

Deep learning methods, such as CNN (CNN-based methods), have made great progress in image analysis, allowing for automatic hierarchical feature extraction. CNN-based approaches have been extensively researched for the tasks of binary blur classification and estimation of pixel-level blur maps in applications of blur detection. Unlike manually created methods, CNNs learn discriminative representations directly from training data, minimising the human activity in the creation of descriptors. The traditional methods based on deep learning used CNNs as a patch-level classifier to assess if the image regions were blurred or sharp [23].

Subsequent studies introduced multiscale architectures to improve spatial consistency. For instance, Huang et al. [24] used a six-layer Convolutional Network to estimate the blur maps at the patch level and combined multi-scale outputs to enhance predictions. Zeng et al. [25] produced a local blur metric applying deep feature extraction and dimensionality reduction. Kim et al. [26] introduced residual skip connections and multiscale reconstruction losses to improve blur region detection performance. Similarly, Shen et al. [27] developed semantic segmentation approaches for blur localisation, but proved to be sensitive to boundary sharpness and texture flattening. Wang et al. [28] proposed the HER-Net and advocated for the boundary refinement for blur pixel image recognition under the guidance of edge edge.

Recent comparative studies have shown complementary strengths between classical Laplacian-based approaches and the CNN-based ones. [29] Although Laplacian operators are sensitive to high-frequency edge information, CNN-based models offer better performance through context-wise information tuning. However, CNN-based approaches require significant amounts of training data, deep architectures, and hyperparameter tuning. Furthermore, some models only incorporate implicit feature identification, which increases both the computationally intensive and interpretable complexities. Data variable, object size variation, and noise effects additionally impact the quality of deep model performance. There are often strategies for Data augmentation to alleviate this.

Nevertheless, visual information may still not be enough on its own to provide a fair representation when physically meaningful degradation features are present. Research on multimodal prediction indicates that combining well-structured numerical data with real-time visual features can have a positive effect on classification performance. Hybrid CNNSVM approaches have been proposed in image classification, which combine CNN’s representation learning ability with SVMs’ margin maximisation capability [30-32] For such architectures, the outputs from the fully connected layer of CNNs are used for an SVM classifier instead of the SoftMax layer. This enables better generalisation performance in high-dimensional feature space while still keeping classification boundaries optimal. However, these advances come with some limitations.

Many of the deep learning-based approaches for blur detection have more complex architectures, which cause a higher number of parameters, more GPU memory, and longer training. Multi-stream networks impose additional computational pressures. In addition, current approaches commonly rely on image-based features only and do not explicitly include physically interpretable blur descriptors adapted from the basic principles of image processing. Despite this, there is still a need for a blur detection framework that combines accuracy, interpretability, and low computational cost. Lightweight and stable solutions are particularly important for DBT imaging, which involves processing large volumes of images. To address this, this study introduces a hybrid CNNSVM model that integrates CNN-extracted image features with a Laplacian-based Blur Factor as structured numerical information. The proposed approach enhances blur discrimination and reduces network complexity and computational expense in DBT image analysis by combining complementary feature representations.

3. Materials and Methods

Blur detection is an important and fascinating subject in computer vision. A key part of blur detection involves identifying effective features to differentiate between distorted and undistorted parts of an image. However, image features are often influenced by various uncertain factors. Therefore, in this paper, a novel hybrid feature approach is introduced, combining image features (obtained via the CNN method) with numerical features (BF, derived from the Laplacian filter) to detect blur in DBT images. The proposed methodology consists of three main steps: data acquisition and processing, hybrid features-comprising automated feature extraction using CNN and the blur factor from the Laplacian filter-and model training for blur detection using the hybrid CNNSVM-BF, followed by performance evaluation. (see Figure 1)

3.1. Deep Learning Methods for Blur Detection

A publicly available DBT image (TCIA Archive – BCS-DBT) was employed to collect the data from datasets containing 22,032 reconstructed DBT volumes belonging to 5,610 studies from 5,060 patients [33]. The source Dicom DBT slices possessed a resolution of 1089px × 2457px, which were converted into grayscale images. Subsequently, the source images were resized to increase focus due to the Laplacian filter's default kernel of 3 × 3. This value was too small for the source image size and was mainly affected by noise. Finally, the dataset was divided by 80% (training) and 20% (validation) into two categories to avoid overfitting for training purposes.

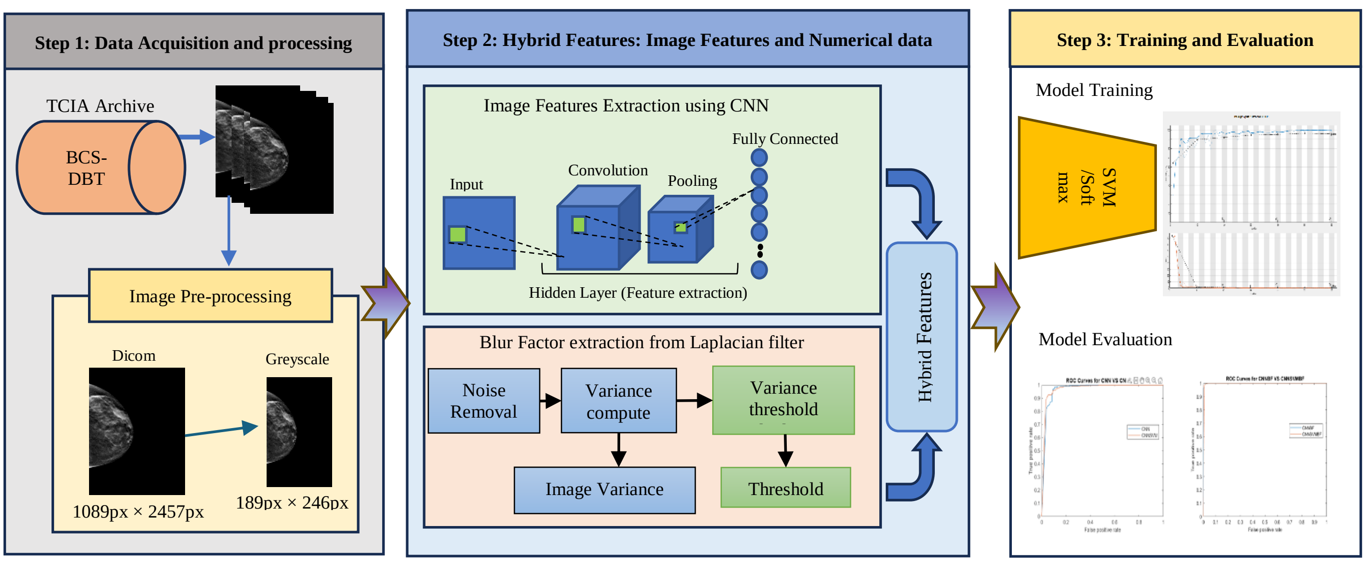

Fig. 1 Flowchart of the proposed methodology for CNNSVM-BF

3.2. Automated Features Extraction using CNN

The convolution-pooling processes of CNN provided significant advantages in feature extraction. This study introduced a custom CNN architecture to extract features from DBT images automatically. Five primary layers were applied in the architecture used for feature extraction, and a Fully Connected layer (FC) was used for classification. Each primary layer of the CNN architecture consisted of a convolution layer, batch normalisation, ReLU, and max pooling. A 246px × 189px image was also sent to CNN as input. The 246 × 189 × 1 input images with 8 kernels of size 3 × 3 × 1 were filtered using the first convolution layer filters. Moreover, the output of the first convolution layer was connected to a batch normalisation layer, followed by the max-pooling layer and the ReLU layer. The second, third, and fourth convolution or max-pooling layers were linked. Lastly, the FC acquired 2 × 4480 = 8962 parameters, which were employed in the subsequent clustering analysis (See Figure 2) displays the custom CNN architecture.

Each layer of a CNN reacted or activated in response to an input image. On the contrary, only a few CNN layers were necessary for visual feature extraction. The fundamental visual elements were determined by the first layer of the network, including edges and blobs. Deeper network layers further processed this primary data, integrating it to yield higher-level image properties. Considering that these higher-level features incorporated all the primitive qualities into a fuller visual representation, they were better suited for recognition tasks. Therefore, blob and edge information could be captured using the trained filters in the first layer of the network. The image features were subsequently extracted from deeper layers using activation techniques at the layer immediately preceding the fully connected networks. Finally, each learned image data of the class was saved as an image feature vector.

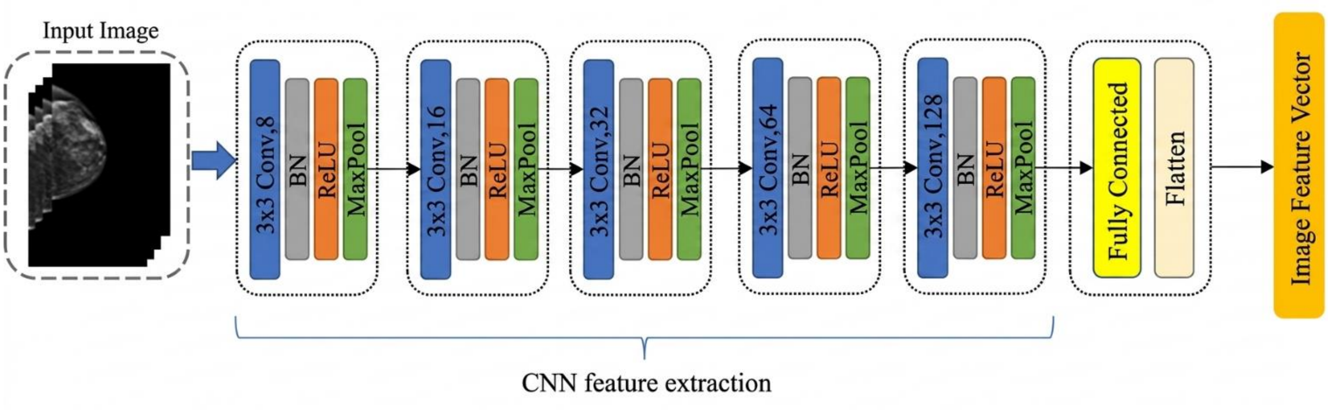

Fig. 2 The architecture of the custom CNN used to generate automatic features of DBT images

3.3. Numerical Features: Blur Factor from Laplacian Filter

This study initiated blur detection by employing a Laplacian operator to locate edges in the image, facilitating edge recognition. The BF was then obtained by computing the intensity variance of the image. An image was considered to possess blurry details if the intensity variance or the BF exceeded a specific threshold (Th) value.

Thus, a significant or low detected variance in a typical representative in-focus image implied many responses (non-edge-like and edge-like features) or limited response dispersion (few edges in the image), respectively [29]. This finding suggested an image was considered blurry if it exhibited only a few distinct edges. Nevertheless, the algorithm choice was solely based on Th.

The domain influenced the selection of a suitable Th. Thus, incorrectly setting the Th could result in the false labelling of the images. For example, an image lacking blurriness was labelled "blurry". Otherwise, a blurry image was assigned to the label "not blurry". Each image containing the intensity variance plotted on an axis with two centres (one for each class) was determined analytically to determine the appropriate Th. The border between classes was then defined using the Th of the weighted mean between the different weight centres.

Therefore, relying on the simplest direct method was inadequate due to its excessive sensitivity to the selection. The subsequent section will utilise BF information with a combination of automated features from CNN (See Figure 3) depicts the flowchart for implementing the Laplacian filter to perform blur detection, and (see Figure 4) portrays the primary processes involved in generating the BF table.

3.4. Blur Detection using the Hybrid Features of CNNSVM-BF

The SVM technique is a widely used data modelling and classification strategy in machine learning. This method possesses exceptional generalisation capacity, which is similar to accurately sorting the samples outside of the feature space used for training. Currently, CNN and SVM are the leading and extensively applied methods for image classification. The key motivation for combining the advantages of CNN and SVM is the rapid incorporation of hidden layers in the CNN model. This incorporation facilitates the extraction of features while simultaneously improving accuracy and performance [31]. Thus, the SVM classifier was substituted for the final layer of the CNN in the hybrid CNNSVM model proposed in this study, This study derived the deep features utilising CNN and then combined those features with the BF determined by applying the Laplacian algorithm. Subsequently, the SVM model used the output of an FC as an input to train the merged feature vectors, resulting in improved classification and decision-making. Owing to its hybrid capabilities, this combination was expected to deliver the most significant results in blur extraction (See Figure 5) illustrates the proposed CNNSVM-BF model. The proposed model was established using MATLAB (R2023a) and trained on a computer with a CPU Intel(R) Core™ i7-10870H 2.3 GHz, a single GPU graphic card NVIDIA GeForce RTX3060, 12 GB RAM, and a Windows 10, 64-bit operating system. Several parameters were utilised for optimising the network based on the ADAM optimiser: a momentum of 0.9, a weight decay of 54, and a learning rate of 0.01 initially. Subsequently, these values were reduced by a factor of 0.1. The training process consumed 10 GB of GPU memory, with the model trained with a batch size of 32, and input images downsized to 246 × 189 pixels.

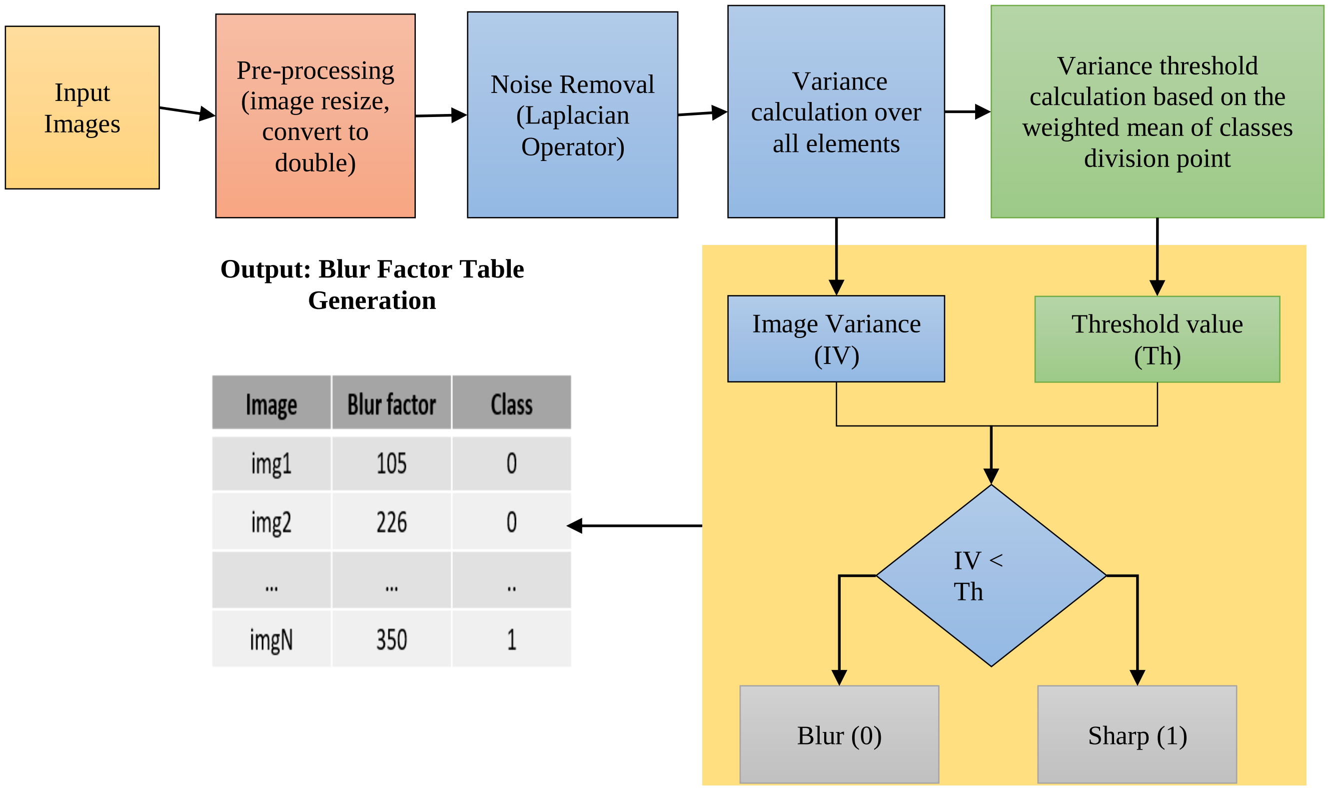

Fig. 3 The flowchart of the Laplacian operator implementation for blur detection

Algorithm 1 Laplacian Blur Factor Algorithm

Input: DBT images Im
Output: Blur factor bf
for *k=1 to numberOfImages* do
Read the input image.
Resize image
Convert image to double (multidimensional matrix)
Find Laplacian variance using the Laplacian filter and the variance function.
Initialize Threshold value Th
if *Iv< Th* then
Label image = 0 (Blurry)
Denote the variance value as the blur factor
else
Label image = 1 (Non-Blurry)
Denote the variance value as the blur factor
end if
end for
Tabulate all the blur factors and status for each input image.

Fig. 4 The pseudocode for blur detection using the Laplacian operator

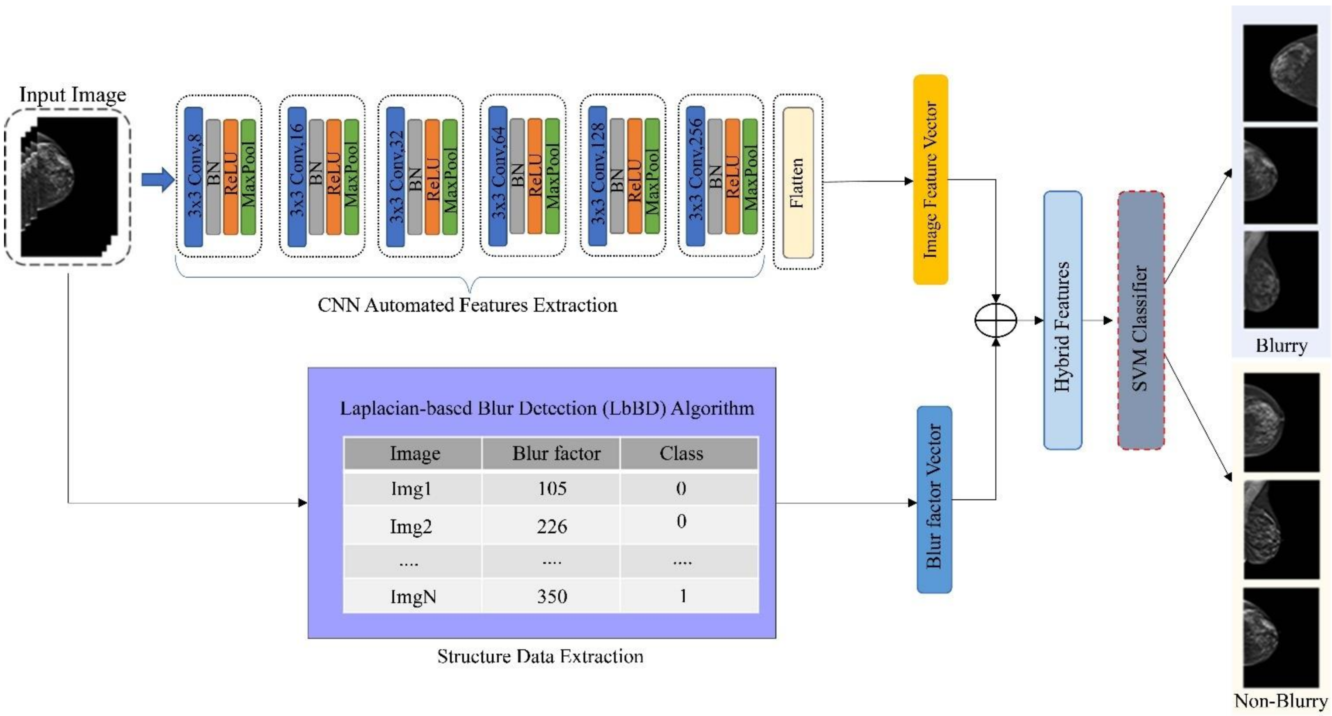

Fig. 5 The proposed hybrid features of CNNSVM-BF

3.5. Performance Analysis

This study was compared and analysed using three experiments. The initial experiment employed the handcrafted features of BF derived from the Laplacian filter. This filter computed the image variance as structured numerical data for blur detection. Consequently, this experiment successfully recognised the ability to detect blurred images and examined the impact of reviewing the initial Th. The second experiment evaluated the effectiveness of CNN with FC and SVM layers in generating automated features from the image. These image features were extracted in the CNN primary layers to classify the blurred image using the CNN or SVM classifier, respectively. Lastly, the third experiment used hybrid features for CNNBF and CNNSVMBF-based analyses: image data extracted by the CNN layer and BF from the Laplacian filter.

The performance of the proposed model was compared and analysed using three standard and commonly used metrics: precision, recall, accuracy, and F1-score. Generally, the comparative methods for performance evaluation adopt these metrics. Hence, the accuracy, precision, and recall are calculated as follows:

Accuracy: Image classification accuracy was determined by calculating the proportion of successfully recognised pixels to the total number of pixels in the image. This process examined every pixel in the image. Hence, the accuracy is expressed as follows:

$$\text{Accuracy}=\frac{TP+FP}{TP+TN+FP+FN} \tag{1}$$

Precision (TPR): The true positive (TP) presented the percentage of adequately categorised pixels. Hence, precision is formulated as follows:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

Recall (FPR): The probability pixel identification that logically displayed typical characteristics but was classified as abnormal was known as a true negative (TN). Hence, the recall was expressed as follows:

$$\text{Recall} = \frac{TN}{TN+FN} \tag{3}$$

F1-Score: Computes the average of precision and recall, where the relative contribution of both metrics is equal to the F1 score. The best value of the F1 score is 1, and the worst is 0. This means a perfect model will have an F1 score of 1 (all the predictions were correct).

$$F1=2*\frac{\text{Precision*Recall}}{\text{Precision+Recall}} \tag{4}$$

4. Result and Discussion

This section presents the experimental evaluation of the proposed hybrid CNNSVM framework for blur detection in DBT images. The performance of the Laplacian-based Blur Factor (BF), image-only deep learning models, and hybrid feature-based models is analysed using quantitative metrics and computational efficiency measures. In addition, the contribution of structured numerical features to classification improvement and reduced computational complexity is discussed in detail.

4.1. Blur detection of DBT images using the Laplacian BF Algorithm

The Laplacian-based Blur Factor (BF) algorithm was first tested as a standalone blur detection method. The Laplacian operator is sensitive to high-frequency edge responses and is known for discriminating between sharp and blurred images, but the performance relies heavily on the selected Threshold Value (Th). An overly low threshold can incorrectly classify blurred images as sharp, while an excessively high threshold can misclassify sharp images as blurred. The optimal threshold for DBT images was assessed using 100 images, including both undistorted and blurred images. The variance of the Laplacian response was calculated for each of the images. Standardised analyses were performed according to the average variance values in the two classes and validated by expert qualitative methodology to confirm clinical relevance for threshold selection. This methodology created reliable ground truth labels for quantitative characterization. The blur detection performance can be visualized in Table 1 for three threshold values (Th = 150, 200, and 250). The threshold value of 200 achieved the best performance generally, having accuracy = 0.97, precision = 1.00, recall = 0.90, and F1-score = 0.95. These observations prove that Laplacian variance encapsulates edge degradation characteristics in DBT images. Yet the varying performance over threshold points to a key problem: the Laplacian method is particularly sensitive to the choice of parameters, and not generalizable to all image kinds. This finding provides evidence for the feasibility of incorporating BF with structured numerical data in a more dynamic context than simply classifying it at the thresholds.

Table 1. Laplacian algorithm performance

Threshold value (Th)	Accuracy	Precision	Recall	F1 score
150	0.75	0.78	0.78	0.78
200	0.97	1.00	0.9	0.95
250	0.90	0.89	0.89	0.89

4.2. Blur Detection of DBT Images Using the Proposed Hybrid Features of CNNSVM

To address the limitations of standalone thresholding, the BF was combined with CNN-extracted image features and assessed using two classifier frameworks: a CNN with a Fully Connected (FC) layer and a CNNSVM. These models include (i) CNN (only image features), (ii) CNNSVM (only image features), (iii) CNN-BF (hybrid features), and (iv) CNNSVM-BF (hybrid features). Performance was evaluated based on accuracy, precision, recall, F1-score, and AUC. Table 2 depicts lower performance on image information-based models than hybrid models.

The CNN model achieved an accuracy of 0.9525, and the CNNSVM achieved an accuracy of 0.9604. Clearly, these findings suggest that implicit feature learning is not enough to entirely differentiate between blurred and non-blurred DBT images, as there is a high degree of similarity in texture and anatomical appearance between slices. Incorporating structured BF features yielded a clear improvement in performance. CNN-BF obtained an accuracy of 0.9736, an increase of ~2.1% over the CNN model. More importantly, the CNNSVM-BF model achieved an accuracy of 0.9921, corresponding to a relative improvement of 3.17% over the image-only CNNSVM model.

Table 2. Comparison of the blur detection performance using different features and deep learning models

Model	Feature Type	Accuracy	Precision	Recall	F1-score
CNN	Automated	0.9525	0.9441	0.9142	0.9288
CNNSVM	Automated	0.9604	0.9750	0.9061	0.9392
CNN-BF	Hybrid	0.9736	0.9844	0.9403	0.9618
CNNSVM-BF	Hybrid	0.9921	0.9921	0.9844	0.9882

While the numerical difference might seem slight, this improvement is significant in DBT imaging since microcalcifications have a small footprint and may be present in only a few pixels. Enhanced recall and F1-score indicate improved sensitivity in detecting blurred slices, therefore minimizing the risk of discarding diagnostically relevant images. The benefit is based on the complementary integration of different features. The BF quantifies high-frequency edge degradation explicitly, which gives physically relevant insight into the image sharpness. CNN features, in sharp contrast, convey abstract textures and a sense of space. When structured blur descriptors are fused with learned features, the classifier is provided with both physical and contextual information, enhancing discrimination performance. The ROC curves depicted (see Figure 6) also support this trend. The CNNSVM-BF model had the best AUC among all models, meaning it performs better at separating blurred and non-blurred classes. While the difference of AUC between CNN-BF and CNNSVM-BF seems small, the higher F1-score and recall indicate that there is more balance between precision and sensitivity as compared to the model without BF. It further indicates that the SVM classifier utilizes the hybrid feature space better than the standard SoftMax layer. These results, in general, indicate that the integration of structured numerical blur descriptors makes the classification more robust than using image-only deep learning approaches.

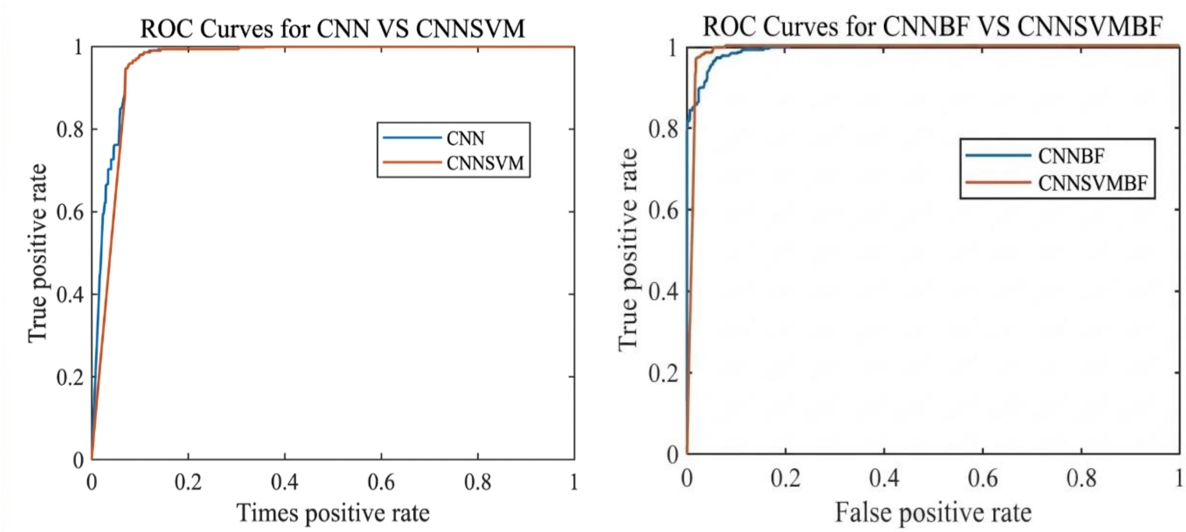

Fig. 6 The ROC comparison of CNN vs. CNNSVM and CNN-BF vs. CNNSVM-BF models

Table 3. Execution time and accuracy comparison across models and epochs

Epoch	Model	Execution Time (s)	Classification Accuracy
15	CNN	272.22	0.9525
	CNNSVM	292.48	0.9604
	CNN-BF	252.53	0.9736
	CNNSVM-BF	269.88	0.9921
30	CNN	431.76	0.9657
	CNNSVM	450.95	0.9472
	CNN-BF	431.05	0.9604
	CNNSVM-BF	449.51	0.9842
50	CNN	656.79	0.9683
	CNNSVM	679.11	0.9868
	CNN-BF	606.49	0.9657
	CNNSVM-BF	633.65	0.9842

4.3. Computational Efficiency and Accuracy-Time Trade-Off

In addition to classification performance, computational efficiency is critical for practical DBT screening applications. DBT datasets contain a considerable number of slices per patient, making it crucial that both the efficiency of training and inference directly contribute to clinical viability. For all models, implementation time with 15, 30, and 50 epochs is shown in Table 3. Figure 7 shows the trade-off between accuracy and execution time. As for all epoch settings, CNNSVM-BF demonstrated a stable accuracy while maintaining a competitive execution time. Comparing different models, CNNSVM-BF achieves performance at 15 epochs of training, which is also the second lowest computational cost by distance (269.88 seconds and 0.9921) than CNN-BF. CNN-BF outperformed all models, although the second lowest execution time was achieved while processing the data (252.53 seconds), but failed to achieve classification accuracy (0.9736). Importantly, the image-only CNNSVM model had the highest execution time in all epochs without significantly increasing accuracy. The decrease in accuracy is further confirmed by the fact that increasing complexity increases the performance of the model unless it is complemented by structured features. Of importance is that at 15 epochs, CNNSVM-BF can obtain the best performance. However, increasing the epoch to 30 or 50 had no significant effect on accuracy, and the hybrid feature integration would further improve convergence efficiency. By embedding BF features, you lift the responsibility from deep layers to learn representations relating to blur subliminally. As a result, the model takes fewer training iterations to achieve stable decision boundaries.

The improved efficiency can be explained by two factors:

Feature Complementarity: As in previous applications, the BF offers explicit information about edge degradation, which reduces the need for deep convolutional layers to indirectly infer blur characteristics.

SVM Margin Optimization: In contrast, replacing the SoftMax layer with the SVM enhances classification margin in high-dimensional hybrid feature space, achieving better generalization with no extra parameter expansion. These results confirm that the proposed hybrid CNNSVM model achieves a favourable balance between classification accuracy and computational efficiency. Compared to image deep learning methods that have to exploit higher network depth or multi-stream architectures, this proposed framework realizes a better performance and lower training complexity.

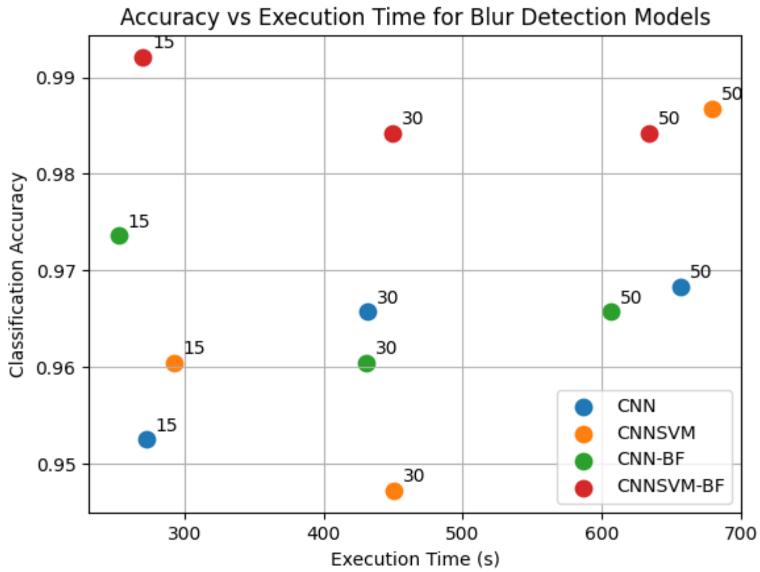

Fig. 7 Classification accuracy versus execution time for different blur detection models evaluated at 15, 30, and 50 epochs

5. Conclusion

This work presented a strong hybrid CNNSVM model for detecting blur in Digital Breast Tomosynthesis images by combining CNN-generated image features with structured numerical information derived from a Laplacian-based Blur Factor. Physically meaningful blur descriptors combined with deep feature representations improved the accuracy, performance, and usability of image-only learning approaches, enabling the detection of blurred and non-blurred DBT slices with subtle structural differences. The experimental results showed that the proposed CNNSVM-BF model outperformed CNN and CNNSVM models that used only the image features for classification. The hybrid approach achieved better accuracy, recall, F1-score, and AUC, indicating improved discrimination power as well as class separability. While the numerical gains can be easily classified as small improvements, they are significant in DBT imaging, where microcalcifications occupy small regions and accurate slice selection is critical. Besides accuracy increases, the suggested framework enhanced computational efficiency. Integrating the Blur Factor into the structured numerical data further minimized the necessity of deeper network learning and improved performance at lower training epochs. A SoftMax classifier replaced with an SVM improved margin-based classification in the hybrid feature space, further boosting generalisation and keeping a stable convergence. The synthesis findings show that leveraging structured blur-related features and a CNN-based approach offers a lightweight yet powerful solution for automated blur detection. By achieving a tradeoff between accuracy and computational cost, this hybrid framework is good for large-scale DBT screening conditions where reliability and efficiency are both critical features.

Author Contribution Statement

Nur Athiqah Harron: Writing-original draft, Methodology, Data curation, Writing-review & editing. Siti Noraini Sulaiman: Writing-review & editing, Methodology, Resources. Muhammad Khusairi Osman: Conceptualization, Methodology, Writing-review & editing. Iza Sazanita Isa: Conceptualization, Writing-review & editing. Noor Khairiah A. Karim: Data curation, Resources.

Conflicts of Interest

All authors declare no competing interests.

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