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Integration of Deep Learning Techniques with Hu Moment Invariants for Automated Cancer Stage Determination

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Abstract: Accurate determination of breast cancer staging from mammographic imagery remains a clinically demanding challenge, owing to substantial inter-lesion variability in morphological appearance, inconsistencies in image acquisition quality, and the inherent limitations of conventional deep learning architectures in capturing diagnostically relevant structural characteristics. Predominant existing methodologies disproportionately exploit texture and intensity-based representations while systematically neglecting rotation- and scale-invariant shape descriptors that carry considerable discriminative value in tumor characterization and malignancy grading. This study seeks to develop a robust, automated breast cancer staging framework that synergistically integrates deep semantic representations with invariant morphological descriptors, with the dual objective of enhancing multi-class classification performance and enabling a more holistic and clinically interpretable characterization of mammographic lesions across BI-RADS categories. A hybrid computer-aided diagnosis (CAD) framework is proposed and evaluated on mammographic images drawn from the King Abdulaziz University (KAU) benchmark dataset. The pipeline is initialized with an autoencoder-based preprocessing stage that performs noise attenuation and perceptual image reconstruction, thereby ensuring high-fidelity input representations for downstream processing. Subsequently, high-level semantic features are extracted via the pretrained EfficientNet-B7 convolutional architecture through transfer learning, while complementary morphological representations are encoded by computing the seven Hu Moment invariant descriptors to capture affine-invariant shape properties of breast lesions. The resultant feature sets are integrated through a principled feature-level fusion strategy, yielding a unified discriminative representation for multi-stage BI-RADS classification. Comprehensive model assessment is conducted employing five standardized performance metrics: Accuracy, Precision, Recall, F1-score, and Specificity. Empirical evaluation on the KAU dataset demonstrated that the proposed hybrid framework attained an overall classification accuracy of 96.0%, accompanied by a precision of 95.5%, a recall of 97.3%, an F1-score of 96.3%, and a specificity of 99.4%. These results consistently surpass those achieved by standalone deep learning architectures and conventional handcrafted-feature methodologies, substantiating the complementary nature of fusing semantic deep representations with invariant morphological descriptors for improved lesion discrimination. The proposed hybrid CAD framework effectively harnesses the representational strengths of EfficientNet-B7 and the geometric invariance of Hu Moment descriptors to advance automated breast cancer stage determination from mammographic images. The empirical findings underscore the diagnostic value of incorporating morphological shape information into deep learning-driven classification pipelines and affirm the clinical translational potential of the proposed methodology as a decision-support instrument for radiologists engaged in BI-RADS-based breast cancer screening and diagnosis.

Keywords: Breast cancer, Deep learning, Mammography, Diagnosis, benign, malignant, BI-RAD

1. Introduction

Due to its high incidence rates worldwide, breast cancer is one of the most common malignancies in women and a major public health problem. Epidemiological studies have proven the necessity of early detection and correct staging for improving therapeutic outcomes and survival. Even though mammography is a standard tool for screening and diagnosis, its interpretation is highly dependent upon radiologists' experience and expertise, which may lead to variability in clinical decision-making [1].

Deep learning algorithms, particularly convolutional neural networks (CNNs), have dominated the recent advances in medical image analysis due to their excellent performance in automated detection and classification tasks. DenseNet and ResNets can learn complicated hierarchies of representations directly from imaging data, limiting reliance on heavy-handed feature engineering, as do EfficientNet and others. Nevertheless, these models mainly address texture and intensity-based features, so they may limit the sensitivity towards subtle changes of morphology critical in tumor staging as well as pathological diagnosis [2][3].

Previous studies demonstrated the prognostic significance of geometrical and morphological features in breast lesions. Malignant tumors frequently have irregular or spiculated borders, often asymmetric, while benign lesions are usually smoother and well-circumscribed. Hu invariant moments (contributors) are a set of shape descriptors that can capture these structural properties relatively robustly, since shape is invariant to translation, rotation, and scaling transformations. However, traditional machine learning methods that depend on handcrafted features may not be well-suited for the high-dimensional and heterogeneous nature of medical imaging [4].

To address these issues, we proposed a multimodal model for predicting breast cancer stage that integrates deep-learning-based feature extraction with custom shape descriptors. First, we use an autoencoder-based approach to enhance mammographic images for noise reduction and contrast maximization. It extracts deep features using EfficientNet-B7 and computes the Hu moments, which are used to extract an invariant form of shape. The set of these complementary feature sets is then combined to create a single multi-modal representation for classification.

The hybrid approach proposed is tested with datasets that contain mammography collected from King Abdulaziz University (KAU). The experimental analyses of the developed ensemble are comprehensive to benchmark it against a baseline deep learning model. Results show that shape-based descriptors contribute to improved classification, leading to consistent improvement across various evaluation metrics and reinforcing the value of using morphological information in predicting breast cancer stage. The main contributions of this study are delineated as follows:

1. A novel hybrid computational framework is proposed, systematically integrating the deep representational capacity of EfficientNet-B7 with the geometric invariance of Hu Moment descriptors, thereby enabling robust and automated multi-stage BI-RADS breast cancer classification from mammographic imagery.
2. An autoencoder-based preprocessing pipeline is introduced as a dedicated image enhancement stage, designed to reconstruct and refine mammographic images through noise suppression and artifact attenuation, ensuring high-fidelity input representations prior to feature extraction.
3. A principled feature-level fusion strategy is devised, synergistically combining high-level semantic deep representations derived from convolutional architectures with low-level morphological shape descriptors possessing affine invariance properties, thereby enriching the discriminative capacity of the consolidated feature space.
4. A rigorous and comprehensive experimental evaluation is conducted on the KAU mammography benchmark dataset, employing a multidimensional suite of performance metrics—encompassing Accuracy, Precision, Recall, F1-score, and Specificity—to ensure statistically grounded and clinically interpretable assessment of classification performance.
5. An extensive comparative analysis is performed against both standalone deep learning architectures and conventional handcrafted feature-based methodologies, systematically substantiating the superiority and generalizability of the proposed hybrid model across varied evaluation conditions.

   The remainder of this paper is organized as follows. Section II reviews the related work on deep learning and shape-based breast cancer classification methods. Section III presents the materials and methods, including dataset description, image enhancement, feature extraction, and fusion strategy. Section IV discusses the experimental setup and results. Section V provides a discussion and limitations of the proposed framework. Finally, Section VI concludes the paper and outlines future research directions.

2. Related Work

2.1 Deep Learning For Breast Cancer Analysis

Deep learning techniques are promising approaches as they can learn discriminative features from raw data directly. Conventional machine learning techniques were outperformed on several breast cancer detection and classification tasks by convolutional neural networks (CNNs). Initial research activity worked on using architectures like VGGNet and AlexNet to classify mammographic images into benign-malignant classes. While these models yielded positive results, they came with high computational cost and a lack of generalizability to multiple datasets [5][6]. Later works have focused on designing deeper and more computationally efficient architectures (e.g., EfficientNet [12], ResNet [13], or DenseNet [15]) that improve the flow of information in the network and allow for a better reuse of features. Specifically, EfficientNet has received attention for its compound scaling strategy that uniformly applies depth, width, and input resolution to the base model [7][8]. Different versions of these architectures have been successfully implemented for breast cancer detection and classification of both mammographic images and histopathological images. However, these features may not allow detailed representation of essential morphological aspects of lesions, which are relevant for cancer staging, meeting the clinical need, such as textural or spatial representation of tissue properties. Still, many deep learning approaches extensively use image intensity and texture features predominantly [9].

2.2 Shape-Based Feature Extraction in Mammography

Traditionally, computer-aided diagnosis systems have relied on handcrafted features for breast cancer detection before deep learning methods became the norm. Of these, shape-based descriptors were relatively well researched as they are highly correlated with tumor aggressiveness. Features, including asymmetry, margin roughness, and complexity of lesion borders, are often used as diagnostic indicators in clinical assessment [10]. Because of their invariance against geometric transformations such as scaling, rotation, and translation, Hu moments have been frequently employed in this context because they are robust shape descriptors. Hu moments are widely employed for moment-based features, and various conventional classifiers, including support vector machines (SVM), k-nearest neighbors (k-NN), and random forests, have been used to classify the breast masses [11] [12]. These methods showed that using shape features was a viable discriminative mode of lesion pattern detection. Yet, the manual nature of these descriptors, as well as the inability of conventional classifiers to better model complex and nonlinear relationships in medical images, restricted the overall performance of such systems.

2.3 Hybrid Handcrafted and Deep Learning Approaches

In order to mitigate the drawbacks of both handcrafted features and deep learning methods, some recent works have proposed such hybrid frameworks which combine the advantages of handcrafted descriptors with deep features. The underlying rationale in them is that handcrafted features represent some domain knowledge, while deep-learning-based methods have high-level abstract representations. The performance of classification in medical imaging tasks can be improved by feature fusion strategies, as shown in several studies [13].

Hybrid models that combine texture, shape, and deep features have shown enhanced breast cancer classification prowess. As an example, hand-crafted shape and texture features have been used in combination with features extracted from convolutional neural networks (CNN) for breast lesion classification with increased robustness and inter-dataset generalization [14] [15]. A lot of the hybrid approaches that exist use shallow CNN architectures, or only care about detection and not cancer stage determination. Although invariant shape descriptors such as Hu moments have been used in isolated cases, even from a deep learning perspective, most of the work is still experimental, and there has been limited introduction of state-of-the-art deep learning architectures like EfficientNet into this space.

2.4 Research Gap And Motivation

Deep learning approaches have made impressive strides towards getting equivalent performance in analyzing breast cancer images; however, they are still not able to encode clinically relevant morphological features. On the other hand, shape-based descriptors (e.g., Hu moments) work on physically defining the geometric formation of the lesion, yet fall short in terms of expressiveness offered by deep models. It has been shown by prior research that there is a lack of systematic combination of invariant shape descriptors with modern deep learning architectures, especially when considering the design of breast cancer stage classification methods using high-performing networks such as EfficientNet-B7.

In order to fill this void, the current work presents a framework that is a hybrid of shape features from Hu moments and deep features obtained via the EfficientNet-B7 architecture, after an image enhancement step via an autoencoder. The goal of this approach is to improve the precision of breast cancer stage predictive systems by combining handcrafted and deep representations, thus offering a more accurate and clinically relevant characterization of lesion characteristics.

3. Materials And Methods

3.1 Datasets Kau

With the proposed framework, this study uses a mammography dataset to evaluate its robustness and generalization performance. The dataset from King Abdulaziz University (KAU) contains annotated mammography images obtained from a clinical setting based on the stage of breast cancer. The dataset approximates differences in imaging conditions encountered in the real world and accounts for the variability inherent to clinical practice [16].

3.2 Image Preprocessing And Enhancement (Autoencoder)

Several research works have tackled the issues of low contrast and noisy mammograms using deep learning-based enhancement approaches. Out of these methods, one of the best unsupervised image enhancers has evolved to be [autoencoders]. They learn compact representations that retain diagnostically relevant features and suppress irrelevant artifacts.

Previous work has shown how autoencoders yield good results in the field of medical imaging, especially when only a few labeled data points are available [17], which is frequently the case for deep learning-based computer-aided diagnosis systems.

Mammographic images have low contrast and high degrees of structural and electronic noise, which limits the ability to discriminate subtle diagnostic features that, in turn, reduces the performance of deep learning-based classification models. To address these limitations, an image enhancement step was included in the preprocessing pipeline to enhance the signal while retaining structural information. A deep autoencoder is used in this paper to match a nonlinear mapping function (f_{θ}) that maps the input image to a lower-dimensional latent space and a decoding function which reconstructs the image. This reconstruction process can be formally described in Eq. (1):

$$g_{\emptyset}\big(f_{\theta}(\,x\,)\big) = {}^{\wedge}\,x \qquad (1)$$

Here, the input image is indicated by “x”, and "$^{\wedge}\,x$" represents the reconstructed output. A reconstruction loss function (for example, mean squared error) is minimized to optimize the network so that only diagnostically relevant textural patterns are preserved while high-frequency noise components are suppressed.

Since they do train in an unsupervised way, where doing supervised training is difficult, especially for the medical imaging domains, having a limited dataset with annotated labels [17]. The proposed improvement stage produces a more stable and general feature representation, which allows for better extraction of features through downstream classification performance while reducing the risk of overfitting.

3.3 Hu Moment Feature Extraction

Hu Moments are then extracted from the enhanced images for characterizing the geometric properties of breast lesions. Hu Moments are a collection of seven invariant descriptors computed using moments of the image, being robust against aforementioned transformations (translation, rotation, and scale) [18]. These invariance properties make them highly desirable for coding breast lesion morphology in mammographic imaging, which undergoes common variations in acquisition conditions and lesion sizes. Background Shape irregularity is a distinctive marker for malignancy and tumor development. Geometric information provided by Hu Moments can be automatically encoded as features, which helps to improve the feature representation space in the proposed framework. This integration overcomes the potential limitations of deep learning models that mostly depend on intensity- and texture-derived features, which may only poorly encompass the structural complexity characterizing pathological shapes [19].

3.4 Deep Learning Architecture (Efficientnet-B7)

The EfficientNet-B7 architecture is used for deep feature extraction and classification due to its efficiency for both computational and prediction purposes. EfficientNet introduces a compound scaling method that uniformly systematically scales these networks, achieving state-of-the-art accuracy with an order of magnitude smaller number of parameters than earlier conventional convolutional neural network (CNN) architectures [20]. It has achieved state-of-the-art performance on various medical image analysis tasks, especially for breast cancer detection and classification as well. In this work, we use the network to obtain high-level semantic representations of the enhanced mammographic images, and it has been used as our main deep learning block in our proposed framework [21].

3.5 Feature Fusion Strategy

A feature-level fusion strategy was used to utilize the complementary characteristics of handcrafted features and deep features. Concatenation of output deep feature vectors from the EfficientNet-B7 network with seven Hu moment invariants derived from the enhanced mammographic images. Min–max scaling was performed on the handcrafted features before fusion to match them with the deep feature representation space. The fused feature vector retains both high-level semantic information and invariant geometric properties of breast lesions. Such a hybrid representation allows the model to better differentiate more subtle morphological differences between benign and malignant tissues, as well as across BI-RADS stages.

3.6 Evaluation Metrics

The evaluation of the proposed framework using standard metrics that are widely used for medical image classification tasks. This covers Accuracy, Precision, Recall, and F1-score. Ultra, detailed in terms of overall classification reliability and class-wise performance. Moreover, we use the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) to assess how well our model can distinguish between different breast cancer stages at different operating thresholds. Using multiple evaluation metrics offers a complete and dependable performance measurement, especially in medical applications where sensitivity and diagnostic accuracy are essential [22]. We refer to the seven Hu Moments in Equs. (2) to (8) as

1. ***Hu3** or **Hu Moment 3***:
   Indicates the skewness of intensity distribution in the image (skew left or right).
2. ***Hu4** or **Hu Moment 4***:
   Describes the degree of asymmetry in the image's intensity distribution.
3. ***Hu5** or **Hu Moment 5***:
   Measures the "cusps" in the image's shape. It is related to the presence of edges in the image.
4. ***Hu6** or **Hu Moment 6***:
   Captures the degree of curvature or smoothness in the image's contour.
5. ***Hu7** or **Hu Moment 7***:
   Represents a combination of higher-order moments and is useful for distinguishing between different shapes.

$$\emptyset_1 = \eta_{20} + \eta_{02} \tag{2}$$

$$\emptyset_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{3}$$

$$\emptyset_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \mu_{03})^2 \tag{4}$$

$$\emptyset_4 = (\eta_{30} + \eta_{12}))^2 + (\eta_{21} + \mu_{03})^2 \tag{5}$$

$$\emptyset_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2) - (\eta_{21} + \eta_{03})^2] \tag{6}$$

$$\emptyset_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\,\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \tag{7}$$

$$\emptyset_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2) - (\eta_{21} + \eta_{03})^2] \tag{8}$$

4. Experimental Results

4.1 Performance With Hu Moments

This section introduces the experimentation setup in detail; it also presents a discussion of the experimental results. The suggested framework was trained using the KAU dataset, as mentioned in the preceding section. The dataset was partitioned into two sets: a training set, which comprised 70% of the data, and a testing set, which comprised 30% of the data. These strategies will improve the model's performance and facilitate its training. The positive data has been incorporated into the validation set to verify the model's ability to differentiate between negative and positive data, as well as its utilization in the testing set. Thus, this configuration will attain data equilibrium and prevent the model from being skewed towards positive data in the validation and testing sets.

The framework underwent training using the DAGRAD optimization technique, with a learning rate of 0.001, a batch size of 128, and a duration of 50 epochs. The input has dimensions of 224 pixels in width, 224 pixels in height, and 1 channel. The model was trained using the Adam optimization algorithm with a learning rate of 0.001 and a batch size of 128 for 50 training epochs. The categorical cross-entropy loss function was employed for multi-class classification, while the Rectified Linear Unit (ReLU) activation function was used within the network layers. The actual cases before and after classification are listed in Table (1).

Table 1. ***The Actual cases before and after classification.***

Total of cases KAU dataset)	Benign cases before classification	Malignant cases before classification	Benign cases after classification	Malignant cases after classification
5662	2000	3662	1620	3540

4.2 Evaluation Metrics

The suggested approach will be presented in this section on a number of different performance indicators.

Accuracy: The proportion of correctly identified samples out of the total number of samples in the test set, as in Eq. (9)

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \qquad (9)$$

Precision (in a positive context) The true positive rate is determined by dividing the number of correctly identified positive samples by the total number of expected positive samples, as in Eq. (10)

$$Precision = TP/(TP + FP) \qquad (10)$$

Recall: it is important to have it in mind (within the positive collective). The accuracy rate is calculated by dividing the number of correctly predicted samples in the positive class by the total number of samples in the positive class, as in Eq. (11)

$$Recall = TP/(TP + FN) \qquad (11)$$

The F1-Score: measures the accuracy of the positive class. The harmonic mean of the precision and recall scores achieved for the positive class, as in Eq. (12)

$$F1 - Score = (2 \times Precision \times Recall)/(Precision + Recall) \quad (12)$$

Specificity: The number of true negatives (TN) in the dataset represents the samples that are correctly predicted to be in the negative class out of all the samples that really belong to the negative class, as in Eq. (13)

$$Specifcity = TN/(FP + TN) \qquad (13)$$

To further evaluate the effectiveness of the proposed hybrid framework, an ablation analysis was conducted by comparing three configurations: (1) EfficientNet-B7 using deep features only, (2) Hu moment features with a traditional classifier, and (3) the proposed hybrid model integrating both representations. Table (2) shows the result of the evaluation metrics. The results show that the hybrid approach consistently outperformed each respective baseline, thus further confirming that integrating invariant shape descriptors not only fuses complementary information but also leads to improving classification robustness and generalization performance. Figure 1 provides an explanation of the training status and the accuracy of the results obtained at each stage. The value of (Epoch 10,30, and 50) was altered in order to ascertain which value would be optimal and how much it is affected.

Table 2. The result of the evaluation Metrics

Malignant cases that using with Hu Moment	**Confusion matrix**				
	Accuracy	**Precision**	**Recall**	**F1-Score**	**Specificity**
3662	0.960	0.955	0.973	0.963	0,994

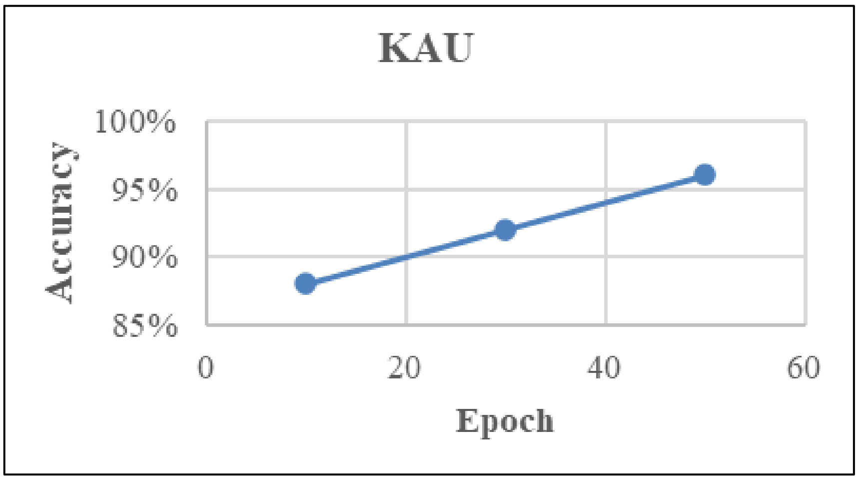

Figure 1. Accuracy of EfficientNetb7 for Hu In Epochs (10, 30, And 50)

5. Conceptual Framework

The proposed framework for breast cancer classification uses the dataset, which was obtained from the Sheikh Mohammed Hussein Al-Amoudi Center of Excellence in Breast Cancer, located at King Abdulaziz University in Jeddah, Saudi Arabia. The data collection period spanned from April 2019 to March 2020, while the annotation process took place between April and June 2020. The dataset has a total of 1416 instances, each of which includes mammography pictures of both breasts (right and left) captured from two different angles (CC and MLO). Consequently, the dataset encompasses a total of 5662 mammogram images. Table (3) lists the dataset description. The information was categorized into five distinct classes based on the BI-RADS classification system. The framework that was used in this model is Google Colab, and the accuracy obtained 96% in the epochs (10,30, and 50).

Table 3. Dataset Description

Item	Value
Total Patients	1416
Total Images	5662
Views	CC and MLO
BI-RADS Categories	1–5
Institution	King Abdulaziz University
Annotation	Expert Radiologists

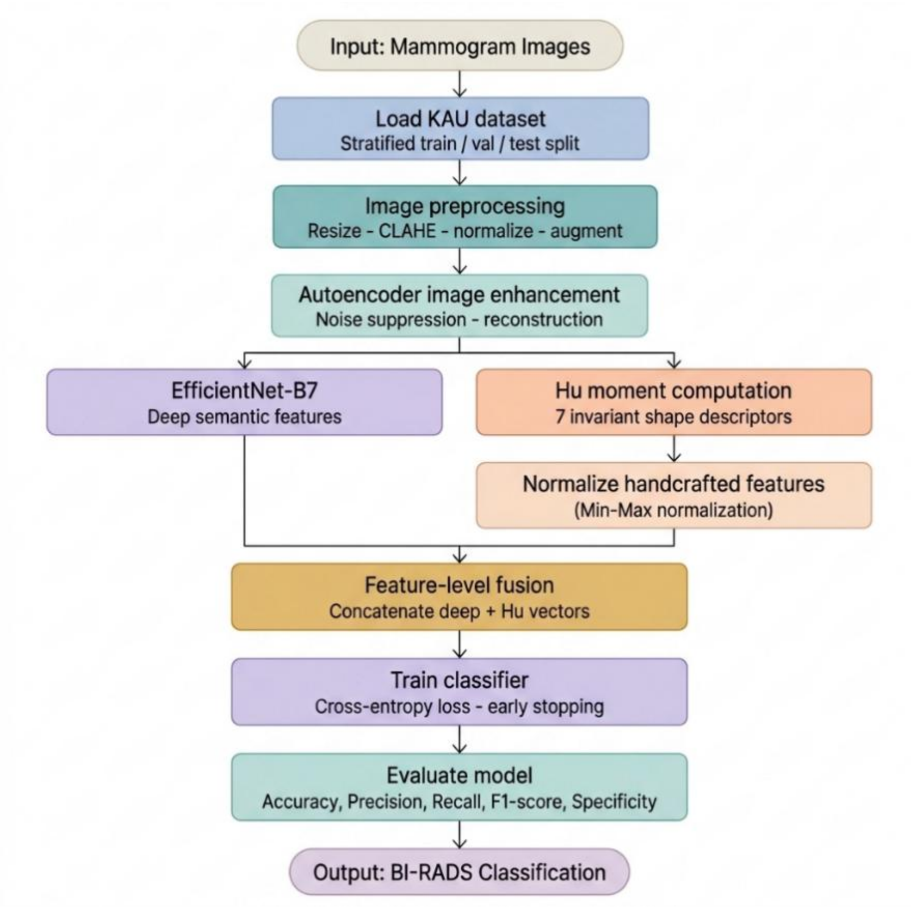

Figure 2. The Proposed Computer-Aided Diagnosis System for Mammogram Classification According to the BI-RADS System

Figure 2 presents the flowchart that organizes the pipeline into five logical phases:

Data preparation— loading the KAU dataset and applying standard preprocessing steps.

Enhancement— the autoencoder reconstruction stage, producing clean, denoised mammograms.

Parallel feature extraction — the diagram splits into two simultaneous branches: the EfficientNet-B7 deep feature pathway and the Hu Moment handcrafted pathway, with a normalization step applied specifically to the invariant descriptors before merging.

Fusion & classification — the two feature vectors are concatenated and fed into the classifier for training with early stopping.

Evaluation — the final model is assessed across all five performance metrics before producing the BI-RADS output label.

The parallel split and merge bars clearly communicate that deep and handcrafted feature extraction occurs independently before being unified at the fusion stage.

6. Comparison Analysis With Previous Studies

The comparison with previous studies is summarized in Table (4). Table (4) includes the following points that summarize the comparison with previous studies, including the algorithms used:

- The comparison indicates that the current study achieved an accuracy of 96%, which is among the highest results recorded in the literature on BI-RADS stage classification.
- Most recent studies have relied on deep learning algorithms (CNN or ResNet) to extract features from mammogram images.
- In contrast, the current study used Hu Moments for feature extraction, a traditional image processing method that demonstrated a high ability to differentiate between BI-RADS stages.
- Some studies achieved lower accuracy (e.g., 76%) due to the complexity of classifying multiple BI-RADS classes or the limited data used.

- Hence, the model considered in this proposal is quick and able to achieve performance that is comparable with many contemporary models, but at a reduced computational complexity.

Researcher & Year	**Dataset / Images**	**Classification Type (BI-RADS)**	**Algorithm Used**	**Accuracy**
Wang et al., 2022 [23]	Mammography Dataset	BI-RADS Classification (0–5)	Deep Neural Network (DNN)	94.22%
Tran et al., 2022 [24]	Mammogram Images	BI-RADS Classification (0–5)	CNN + Data Augmentation	91–93%
Gunawardhana & Zolek, 2023 [25]	Mammography Dataset (2945 images)	BI-RADS Classification	ResNet50 / EfficientNet / Vision Transformer (ViT)	76.39%
Hsu et al., 2024 [26]	Breast Ultrasound Images	BI-RADS (2, 3, 4/5)	ResNet-50 + Ensemble Model	81.80%
Li et al., 2025 [27]	Mammography Images	BI-RADS Classification (3–4	Multi-view CNN	Up to 96.82%
Current Study [28]	KAMD Dataset	BI-RADS Stage Classification	Hu Moments + Classification Algorithm	96%

Table 4. Comparison with previous studies, including the algorithms used.

7. Discussion

The experimental results indicate that using invariant shape descriptors in deep learning models can greatly improve the performance of mammographic image classification. Convolutional neural networks are good at learning texture and intensity patterns; however, they may not correctly represent the geometric properties of clinically relevant breast lesion malignancy characterization. Hu moment invariants are a compact description of lesion morphology invariant under geometrical transformations such as rotation, translation, and scaling.

Combining both deep and handcrafted features enables the proposed framework to leverage both through global semantic information and explicit geometric descriptors. This complementary representation enhances the model's capacity to identify subtle BI-RADS categories, which share similar visual patterns. More specifically, the high specificity obtained in the experimental results proves that the model can effectively reduce false positive diagnoses, which is critical in clinical screening systems. Finally, the hybrid deep-learning frameworks identified in this work may lead to an innovative direction for developing computer-aided diagnosis systems for medical imaging applications.

8. Limitations

While the results are promising, several caveats must be taken care of. Firstly, the experiments were conducted using a single dataset that could constrain how applicable the model is to other clinical imaging scenarios. Second, although the database is sufficient for implementing experiments, this dataset size is still small compared to high-throughput medical imaging repositories. In the future, we will validate the framework proposed herein on several public mammography datasets and investigate different additional invariant descriptors and attention-based deep learning architectures to achieve better classification performance.

9. Conclusion

In mammographic stage classification of breast cancer, this work proposed a hybrid deep learning framework by combining EfficientNet-B7 with Hu moment invariant features. The new system consists of a denoising autoencoder for image enhancement, along with a feature fusion strategy that fuses deep semantic representations and handcrafted geometric descriptors. Experimental evaluation on the KAU mammography dataset showed that the hybrid model's classification performance is higher than traditional deep learning methods. The results underscore the need for domain-specific shape features to be integrated with contemporary deep learning architectures to enhance medical image analysis. The proposed framework can be used by radiologists to assist them in clinical decision-making and ultimately result in a more reliable diagnosis of breast cancer.

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Conflicts Of Interest
The author declares no conflict of interest.

Data Availability Statements
The dataset used in this study is the King Abdulaziz University Breast Cancer Mammogram Dataset (KAU-BCMD). This dataset is publicly available and can be accessed through the following publication: Alsolami, A., Alshamri, S. M., Ghareeb, A., Almutairi, M., Ahmed, S., Alkhamisi, H., Alharbi, R., and Alqarni, B. R. (2021). King Abdulaziz University Breast Cancer Mammogram Dataset (KAU-BCMD). Data, 6(11), 111. Access to this dataset is available from the corresponding repository and publication under the terms and conditions specified by the dataset providers.

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