BreCAI: An AI-Powered Platform for Clinical Decision Support in Breast Cancer Diagnosis

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Abstract. Invasive Ductal Carcinoma (IDC) is the most common and aggressive subtype of breast cancer, requiring early and reliable diagnosis to support clinical decision-making. This paper presents BreCAI, an AI-powered digital pathology platform designed to assist IDC diagnosis through an end-to-end workflow integrating secure access, histopathological image upload, automated AI-based analysis, result visualization, and structured report generation. The platform embeds a deep learning diagnostic engine based on transfer learning to perform patch-level analysis and produce probabilistic IDC predictions. BreCAI was evaluated under real Algerian clinical conditions using independent histopathological slides, demonstrating stable behavior and practical usability for routine pathology workflows.

Keywords: Invasive Ductal Carcinoma, Digital Pathology Platform, Deep Learning, Histopathological Images, BreCAI.

1 Introduction

Breast cancer is the most commonly diagnosed malignancy worldwide and a leading cause of cancer-related mortality [1]. In women, it accounts for nearly 12% of all newly reported cancer cases globally [2].

Breast cancer mainly manifests as ductal carcinoma in situ (DCIS) and invasive ductal carcinoma (IDC) [3]. While DCIS represents a small fraction of cases, IDC is the most prevalent and aggressive subtype, characterized by the invasion of malignant cells into surrounding breast tissue [4].

Early detection plays a critical role in improving treatment outcomes [5]. Diagnosis primarily relies on the visual examination of histopathological slides, where tissue samples stained with hematoxylin and eosin (H&E) are analyzed under a microscope to identify malignant patterns [6, 7]. However, this process is time-consuming and subject to inter- and intra-observer variability [8].

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To address these challenges, artificial intelligence (AI), particularly deep learning, has emerged as a powerful tool. Convolutional neural networks (CNNs) can automatically learn hierarchical features from complex image data, enabling accurate and reproducible diagnoses and improving the detection of early-stage malignancies [9].
Despite significant progress, most existing works focus on model performance evaluated on public datasets, with limited attention to their integration into complete clinical workflows.
In our previous work [10], we developed and clinically validated a deep learn- ing model for IDC detection. Building upon this, we propose BreCAI, an AI- assisted diagnostic platform that integrates this model into a complete clinical workflow. Unlike standalone approaches, BreCAI is designed to support pathol- ogists in routine practice, bridging the gap between research and real-world clinical application.

2 Related Work

Recent advances in artificial intelligence have significantly improved digital pathol- ogy for breast cancer analysis, with invasive ductal carcinoma (IDC) being a major focus of deep learning research.

Early studies primarily addressed whole-slide image (WSI) analysis. Cruz-Roa et al. [11] introduced one of the first CNN-based frameworks for automatic IDC detection using patch extraction and probability maps. Later works shifted toward patch-level classification, with architectures optimized for histopatho- logical data. Ouf et al. [12] proposed CancerNet, a lightweight CNN based on depthwise separable convolutions, achieving improved performance compared to conventional transfer learning models.

More recent studies explored modern CNN architectures. Voon et al. [13] highlighted EfficientNetV2-B0 as a good trade-off between accuracy and effi- ciency, while Mahbub et al. [14] reported strong performance using Efficient- NetB0 with reduced complexity. In addition, domain-adapted training strate- gies have been investigated. Jawad et al. [15] improved CNN performance using histopathology-driven training, and Kanadath et al. [16] showed that fine-tuning pretrained models, particularly DenseNet-based architectures, outperforms fixed feature extraction.

Despite these advances, most works focus on improving model performance, with limited attention to their integration into clinically usable systems. Existing digital pathology tools such as QuPath [17], Cytomine [18], SlideRunner [19], and ASAP [20] mainly support visualization and annotation tasks, rather than complete AI-assisted diagnostic workflows.

Only a few studies have explored interactive AI-based systems. Dequit and Nafa [21] proposed a CNN-based prototype with a graphical interface for pre- diction visualization; however, it remains limited to experimental use.

Overall, there is still a gap between high-performing deep learning models and their deployment in real clinical environments. This limitation motivates the development of integrated platforms such as BreCAI.

3 Model Development

This section presents the development of the deep learning model used for automated IDC detection. The model was developed as an independent analytical component, ensuring robustness and facilitating its integration into the BreCAI platform.

3.1 Dataset Used

The AI model integrated into the BreCAI platform was trained and evaluated using the Breast Histopathology Images dataset, a publicly available dataset hosted on Kaggle [22]. The dataset consists of 277,524 color image patches of size 50 × 50 × 3, extracted from 162 whole-slide images of breast tissue biopsies. These patches include both IDC-positive and IDC-negative regions.

This dataset is therefore well suited for training and validating the deep learning model deployed within the BreCAI platform.

3.2 Model Architecture

Our proposed diagnostic model is based on a convolutional neural network built upon an EfficientNetB0 backbone, as illustrated in **Figure 1**. This architecture was selected due to its compound scaling strategy, which provides a favorable balance between representational capacity and computational efficiency [23].

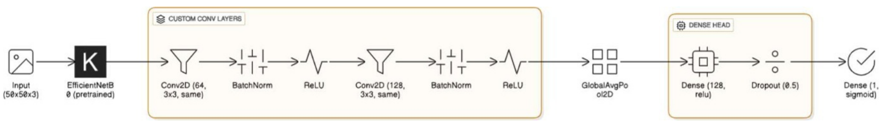

Fig. 1: Overview of the model architecture.

To adapt the pretrained backbone to the histopathological domain, additional convolutional layers were incorporated to refine domain-specific features. These layers enhance the model's sensitivity to tissue morphology and structural abnormalities associated with invasive carcinoma. Feature aggregation is subsequently applied through global average pooling to generate a compact representation for each image patch, followed by a dense classification head producing a probabilistic output indicating the likelihood of IDC-related patterns.

The selection of the proposed architecture is based on a comparative evaluation of multiple deep learning models, as detailed in our previous work [10]. In contrast, the present study focuses on it's integration into the BreCAI platform.

Table 1: Classification performance of the proposed model

Class	Precision	Recall	F1-score	Support
IDC (--)	0.96	0.88	0.92	39,663
IDC (+)	0.75	0.92	0.82	15,842
Accuracy			**0.89**	**55,505**
Macro Avg	0.86	0.90	0.87	55,505
Weighted Avg	0.90	0.89	0.89	55,505

3.3 Experimental Results

To ensure a clinically relevant evaluation, the proposed model was assessed using performance metrics commonly adopted in medical image analysis. The quantitative results summarized in **Table 1**.

At the class level, the model shows a high recall of 0.92 for IDC-positive samples, indicating strong sensitivity in detecting malignant regions. For IDC-negative samples, the model achieves a precision of 0.96 and a recall of 0.88, highlighting its ability to reliably identify non-cancerous tissue.

In addition, the macro-averaged and weighted-averaged metrics indicate con- sistent performance despite class imbalance. These results confirm the robustness and clinical relevance of the proposed model for automated IDC detection from histopathological images.

4 Platform Design and Implementation

Following the training and validation of the proposed deep learning model, we designed and implemented BreCAI, an AI-assisted diagnostic platform intended for practical clinical use. The platform bridges the gap between algorithmic development and real-world deployment.

This section presents the overall system architecture, the AI inference workflow, and the key functional modules supporting clinical interaction.

4.1 Overall Platform Architecture

The BreCAI platform adopts a layered and modular architecture designed to ensure scalability, security, and seamless integration of AI-based histopathological analysis into clinical workflows, as illustrated in **Figure 2**.

At a high level, the architecture is organized into five main layers:

1. **Secure Access Layer:** Ensures secure authentication and role-based access control, regulating user permissions and protecting sensitive medical data.
2. **BreCAI Core Layer:** Manages patient records, coordinates the diagnostic workflow, and orchestrates interactions between platform components.

AI Diagnosis Layer: Constitutes the analytical core of the system. It han- dles automated preprocessing, patch-level analysis, and inference using the deployed deep learning model.

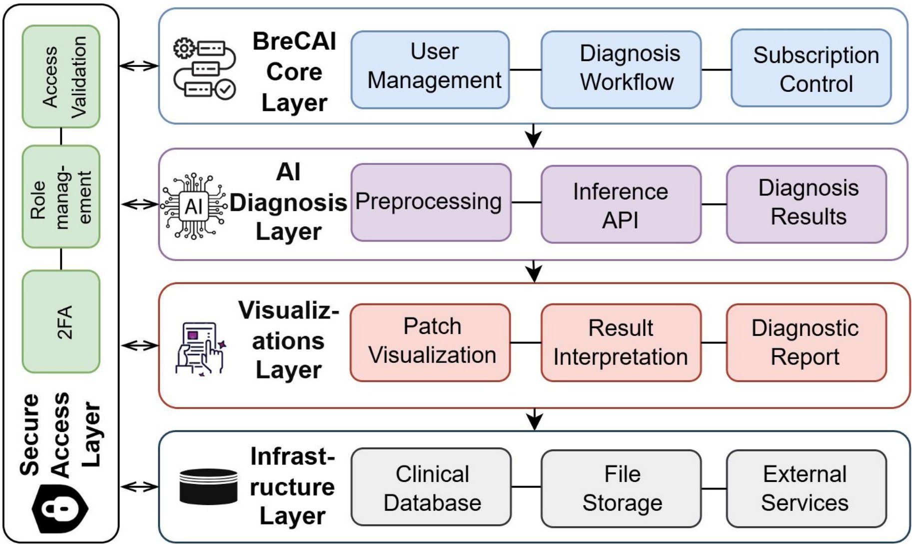

Fig. 2: Overall Architecture of the BreCAI platform.

3. **Visualization Layer:** Presents diagnostic results through interpretable vi- sualizations and generates structured diagnostic reports with patch-level an- notations.
4. **Infrastructure Layer:** Provides data storage, file management, and inte- gration with external services required for reliable platform operation.

This layered design ensures a clear separation of concerns while providing a secure and extensible foundation for AI-assisted diagnosis in real clinical settings.

4.2 System Workflow

The system workflow describes how the proposed architecture is translated into operational functionalities within the BreCAI platform.

The workflow begins with secure user authentication managed by the Secure Access Service, enforcing role-based access control and two-factor authentication via email or phone verification. Authenticated user interactions and diagnostic re- quests are then orchestrated by the Core Platform Services, which handle patient data management, permission enforcement, and clinical workflow execu- tion.

AI diagnostic services are activated only after successful subscription val- idation and secure payment confirmation via the ChargilyPay API, ensuring controlled, traceable, and auditable use of the AI engine.

Once authorized, the application layer communicates with the deployed deep learning model through a dedicated Inference API (FastAPI). Uploaded histo- patho- logical images undergo automated preprocessing and patch extraction before

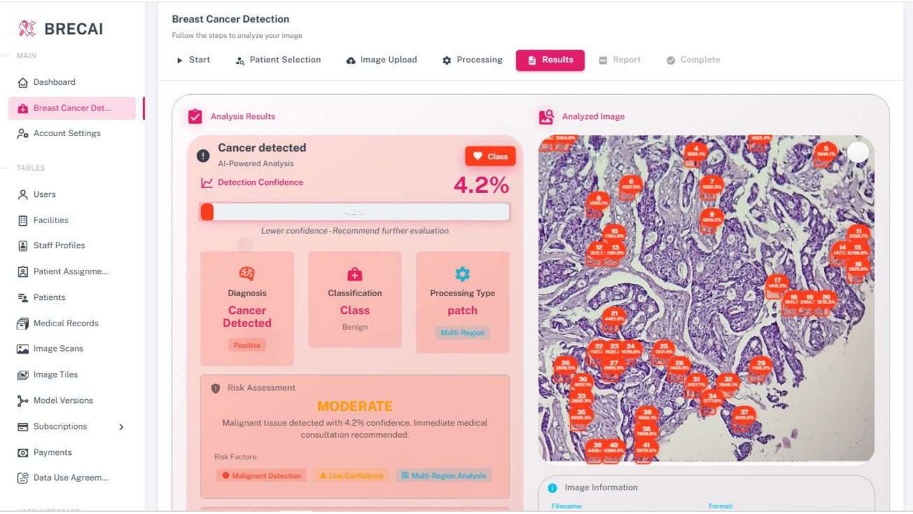

Fig. 3: AI diagnosis interface of the BreCAI platform.

being forwarded for patch-level inference. The model produces probabilistic predictions for each patch, indicating the likelihood of malignancy.

As illustrated in **Figure 3**, the diagnosis interface supports patient selection, image upload, automated processing, and result visualization. Real-time progress indicators inform users about the analysis status, while final diagnostic outputs are presented in a structured and interpretable manner.

Finally, patch-level predictions are aggregated into a structured diagnostic report. This report includes visual annotations highlighting regions of interest according to their predicted malignancy probability. An example of the auto- matically generated report is shown in **Figure 4.**

5 Experimental Evaluation of BreCAI Platform

This section provides an experimental evaluation of the BreCAI platform, focusing on its reliability, robustness, and practical applicability.

5.1 Evaluation Protocol

This experimental Evaluation was conducted in collaboration with an experienced Algerian pathologist from a specialized oncology center. Independent histopathological slides were used to evaluate the BreCAI platform under real- world clinical conditions. These data reflect realistic variability in tissue prepara- tion, staining quality, and acquisition settings commonly encountered in routine pathology practice.

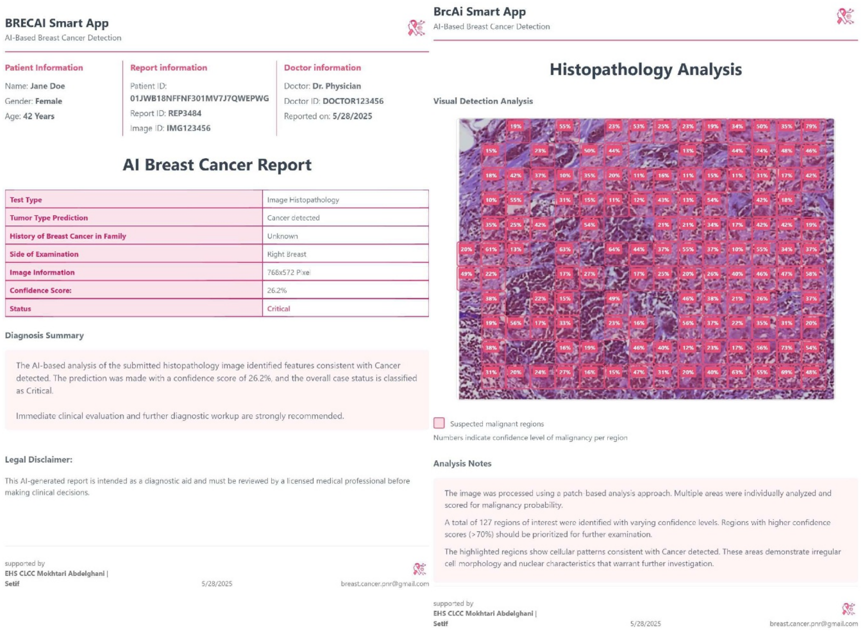

Fig. 4: Example of diagnostic report generated by BreCAI

Each slide was digitized at high magnification and processed through the complete BreCAI workflow, including image upload, patch-level analysis, AI in- ference, and automated report generation. Beyond classification performance, the validation focused on the coherence, interpretability, and clinical relevance of the platform outputs.

5.2 Evaluation Criteria

The platform was evaluated according to the following criteria:

- **Diagnostic relevance**: consistency between AI predictions and expert patho- logical assessment.
- **Reliability**: stability and coherence of results across slides with varying quality and staining conditions.
- **Usability**: clarity of the user interface and ease of interaction during routine diagnostic tasks.
- **Clinical support value**: usefulness of AI-generated outputs (predictions, visual feedback, reports) in assisting diagnostic decision-making.
- **Time efficiency**: perceived reduction in analysis time compared to

conven- tional manual examination.

Overall, this evaluation protocol enables a comprehensive assessment of BreCAI as a clinically oriented AI diagnostic platform, addressing both technical performance and practical usability in real-world pathology settings.

5.3 Results and Discussion

The experimental evaluation was performed on twenty-four (24) histopathological slides, enabling an initial comparison between manual diagnosis and the BreCAI-assisted workflow (**Table 2**). The BreCAI platform achieved an agreement rate of 87.5% with expert assessment. The remaining cases were associated with low-quality slides presenting ambiguous histopathological features, which were also considered diagnostically uncertain by the pathologist.

Table 2: Comparative clinical evaluation of manual diagnosis and BreCAI

Evaluation Criterion	Manual Diagnosis	BreCAI Platform
Diagnostic relevance	✓	–
Reliability across slides	✓	✓
Usability	–	✓
Clinical support value	✓	✓
Generalizability	✓	–
Time efficiency	–	✓

This comparative analysis was conducted by practicing pathologists. How- ever, due to the limited number of tested slides, the diagnostic relevance and generalizability of BreCAI could not be fully established in this study. Despite this limitation, the present evaluation supports the feasibility of BreCAI as a diagnostic support platform under real-world pathology conditions.

6 Conclusion and Perspectives

This work introduced BreCAI, a comprehensive AI-powered platform designed to support breast cancer diagnosis from histopathological images within real clinical workflows. By combining automated image analysis, secure access management, visual interpretation of results, and structured report generation, BreCAI pro- vides an integrated environment that bridges artificial intelligence research and practical digital pathology.

At the core of the platform, a deep learning–based model adapted from the EfficientNetB0 architecture was developed for the automated detection of IDC. The platform was further assessed through external validation and clinical test- ing on Algerian histopathological slides, conducted in collaboration with medical experts. These evaluations confirmed the robustness, stability, and clinical rele- vance of BreCAI under real-world conditions.

Future work will focus on extending BreCAI to larger and multi-center clinical datasets, transitioning from patch-level analysis to whole-slide image processing, and integrating explainability techniques and additional clinical data to further enhance trust, robustness, and clinical applicability

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