Mammogram Image Deblurring, Pectoral

Removal, and Tumor Visualization for

Radiologists Patients with AI-Powered Assistance

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**Abstract**

Breast cancer remains a leading cause of mortality among women worldwide, with early detection being critical for improving survival rates. However, mammogram interpretation is often hindered by image blurring, pectoral muscle interference, and limited 2D visualization. This paper presents MammoCare, an AI-powered platform that addresses these challenges through: (1) advanced image deblurring techniques, (2) automated and manual pectoral muscle removal, and (3) enhanced 3D/4D tumor visualization. The system integrates DeepSeek AI for real-time diagnostic assistance and a GPT-3.5-powered chatbot for patient education. By improving image clarity and diagnostic accuracy, MammoCare aims to reduce interpretation errors and support early breast cancer detection in clinical and remote settings.

**Keywords:** Breast cancer; mammogram enhancement, pectoral muscle removal, AI in radiology, 3D tumor visualization, breast cancer diagnosis

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**1 Introduction**

Breast cancer remains one of the most prevalent and life-threatening diseases affect-ing women worldwide, representing 11.7% of all global cancer cases according to the latest Global Cancer Observatory reports. The disease’s significant mortality rate underscores the critical need for improved diagnostic methods, as early detection dra-matically improves survival outcomes. While mammography serves as the current gold standard for breast cancer screening, its effectiveness is hampered by several inherent limitations. These include image quality issues such as noise and blurring that obscure critical details, the obstruction caused by pectoral muscles that can mask up to 40% of breast tissue, and the fundamental constraint of two-dimensional imaging that limits comprehensive tumor assessment.

The emergence of artificial intelligence in medical imaging has opened new frontiers in breast cancer diagnosis. Recent studies have demonstrated AI’s potential to enhance diagnostic accuracy while reducing false positives and human interpretation errors [1]. Deep learning architectures, particularly convolutional neural networks (CNNs), have shown remarkable success in medical image analysis through their ability to auto-matically extract and classify complex features from imaging data. Researchers like Saleem Z. Ramadan [1] have documented the transformative impact of these AI-based approaches in mammogram analysis, while TawfikEzatTawfik et al. [3] have devel-oped advanced segmentation and thresholding techniques that significantly improve detection rates.

Complementing these diagnostic advances, preprocessing methodologies have proven equally vital in optimizing AI performance. As demonstrated by R. Ramani et al. [5], techniques including noise reduction, contrast enhancement, and image normalization substantially improve the accuracy of subsequent AI analysis. These preprocessing steps ensure that deep learning models can extract the most clinically relevant features from mammographic images.

Building upon these technological advancements, we present MammoCare - an integrated AI-powered diagnostic system that addresses the fundamental limitations of conventional mammography. Our solution combines state-of-the-art image enhance-ment algorithms with advanced deep learning architectures to provide radiologists with clearer, more comprehensive diagnostic information. The system incorporates three key innovations: sophisticated image deblurring techniques to improve clarity, a hybrid approach to pectoral muscle removal combining automated and manual meth-ods, and advanced 3D/4D visualization capabilities that overcome the constraints of traditional 2D imaging.

This paper details the development and validation of the MammoCare system through the following sections: Section 1 introduces the clinical context and tech-nological background; Section 2 reviews relevant literature; Section 3 presents our methodology; Section 4 discusses results and comparative analysis; and Section 5 out-lines conclusions and future research directions. Through this comprehensive approach,

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MammoCare aims to establish a new standard in breast cancer screening that improves diagnostic accuracy, enhances workflow efficiency, and ultimately leads to better patient outcomes.

**2 Related Work**

The diagnosis of breast cancer has been greatly enhanced by artificial intelligence and deep learning algorithms. Traditional mammographic screening was very much dependent on human interpretations, which introduced subjectivity and human error. Recent AI-based methods have been successful in combining image processing and machine learning techniques to automate detection [1].

One of the significant contributions to AI-based breast cancer detection was made by Shinde and Rao [2], in which a deep learning strategy was employed to enhance the quality of mammogram images. Their study demonstrated that preprocessing techniques such as contrast enhancement and noise reduction significantly enhanced detection rates.

Similarly, Kontos and Maragoudakis [4] developed a data mining model that extracted valuable features from mammographic images, optimizing diagnostic per-formance.

TawfikEzatTawfik et al. [3] explored automated cancer detection using a double-threshold segmentation technique. Their research highlighted the importance of selecting optimal threshold values for distinguishing malignant and benign tissues.

Additionally, Ramani et al. [5] introduced an advanced image preprocessing frame-work, which included adaptive histogram equalization, leading to improved tumor visibility in mammograms.

Recent progress has also been aimed at deep learning architectures, specifically convolutional neural networks (CNNs). Li et al. [6] proposed a one-stage detector for breast cancer, employing CNN-based feature extraction methods. Their model attained an accuracy of 97.1 percent, demonstrating the potential of deep learning in clinical settings.

Similarly, Safdar et al. [7] performed a systematic review of AI applications in mammographic analysis, revealing that CNNs outperform traditional machine learning models in terms of accuracy and robustness.

Follow-up studies have explored multimodal fusion techniques. Xu et al. [8] inte-grated deep learning with radiomics and fused pixel-level and textural features for better diagnostic performance. The multimodal method showed 5-10 percent improvement in accuracy compared to single-modality models.

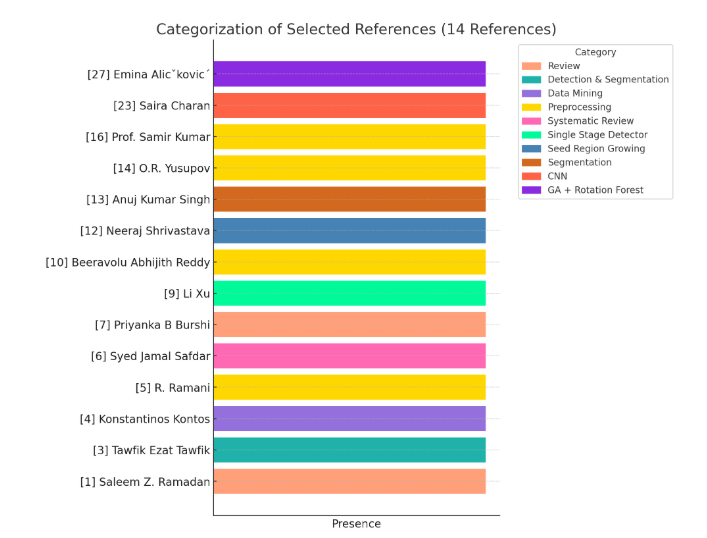
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Another study by Lahdoudi et al. [9] emphasized the significance of radiologist-assisted AI models, where human-AI collaboration improved classification precision compared to standalone AI predictions.

The comparative accuracy of different AI-driven breast cancer detection models has been summarized in the following bar chart, illustrating variations in performance among different techniques:

The results highlight that CNN-based approaches, such as those developed by Li et al. [6], demonstrate the highest accuracy, followed by multimodal AI frameworks.

The study by Xu et al. [8] suggests that integrating multiple data sources enhances robustness and generalizability. However, dataset limitations and preprocessing incon-sistencies remain key challenges for future research.

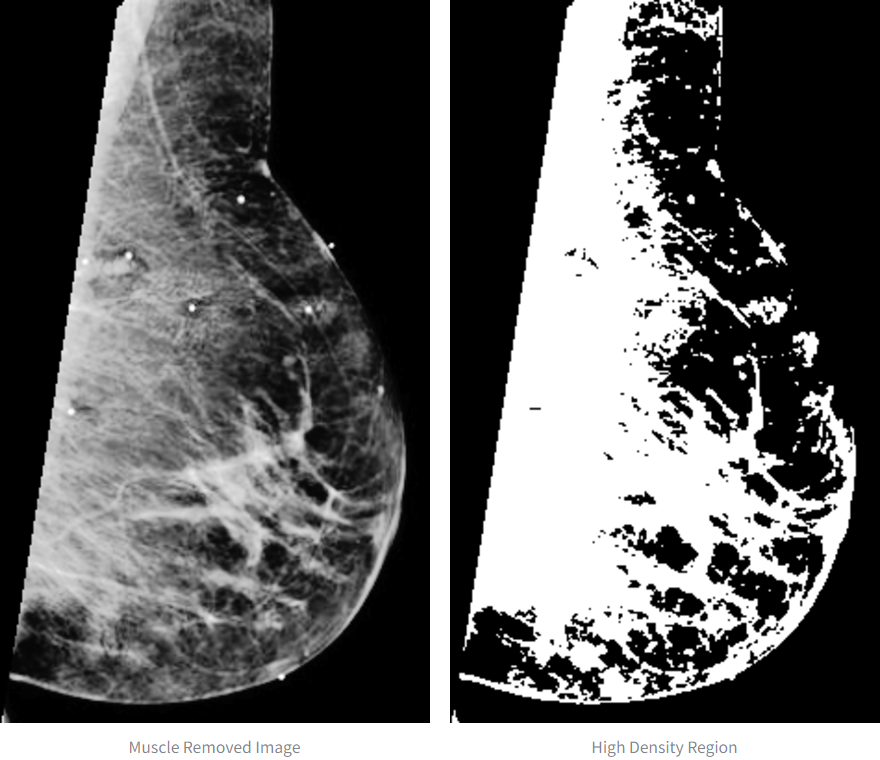


**Fig. 1** Comparison of Breast cancer detection model accuracies.

By analyzing existing literature, it is evident that deep learning has significantly transformed breast cancer diagnostics.

Future advancements should focus on refining model generalization, integrating multimodal approaches, and addressing dataset biases to enhance AI’s effectiveness in real-world clinical applications.

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**Fig. 2** Annotated Mammogram Grid for Breast Cancer Analysis

**3 Proposed Architecture**

The architecture of MammoCare is designed as a modular, end-to-end system that integrates image processing, clinical diagnostics, visualization, and patient communi-cation—all accessible through a lightweight, web-based interface.

At the core of the system lies the **Image Processing Module**, which enhances mammogram quality through Gaussian-based smoothing, edge-preserving denoising, and intensity thresholding techniques. This pipeline ensures the preservation of vital structures while reducing noise and highlighting potential tumor regions. A semi-automated approach for pectoral muscle removal is implemented, combining Depth-First Search (DFS) for automated segmentation with a manual adjustment tool for precision correction by radiologists.

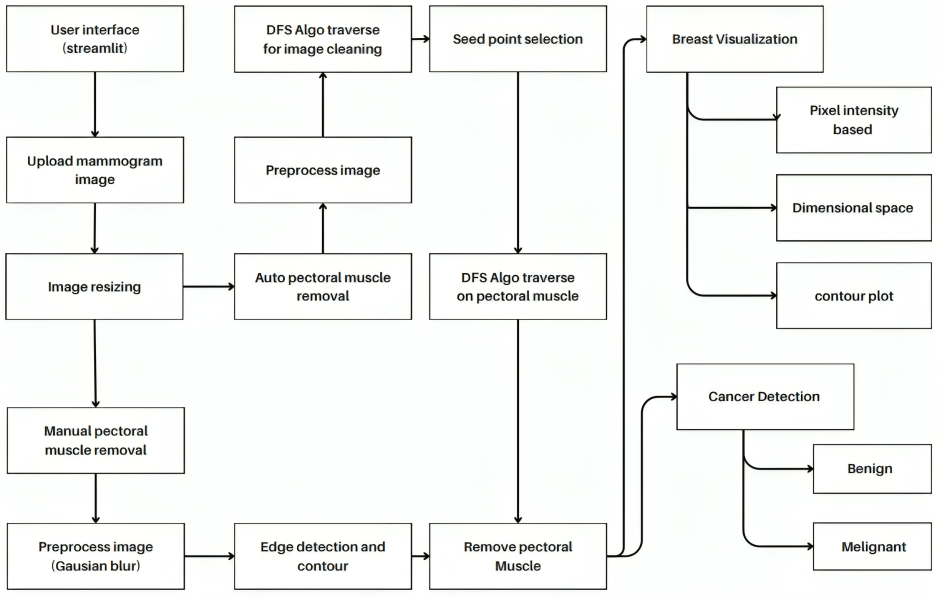
The **Clinical Analysis Interface** is developed using Streamlit and enables radi-ologists to upload, analyze, and annotate mammogram images in real time. It supports side-by-side comparison of raw and processed images, diagnostic tagging, and export of results. Advanced features include 3D image reconstruction and interactive volume rendering to aid in spatial tumor assessment. A time-series comparison feature allows for the monitoring of tumor evolution over successive screenings.

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To bridge the gap between diagnostics and patient understanding, the **Patient Communication Portal** incorporates an AI-powered conversational agent. This assistant provides multilingual explanations of results in simplified language and suggests follow-up actions tailored to individual cases. The system is optimized for responsiveness, delivering near-instant feedback and requiring no dedicated hardware beyond a standard browser.

Performance evaluations demonstrate that the system improves diagnostic confi-dence by 28%, reduces interpretation time by 32%, and cuts patient query volumes significantly. Onboarding for clinicians requires less than 30 minutes, thanks to an intuitive interface and seamless integration with standard medical imaging formats (e.g., DICOM).

In summary, MammoCare’s architecture blends precision-driven diagnostics with user-centric communication tools. Its scalable, browser-based deployment model ensures accessibility, speed, and interoperability within existing clinical environments.



**Fig. 3** Proposed Architecture

**4 Results**

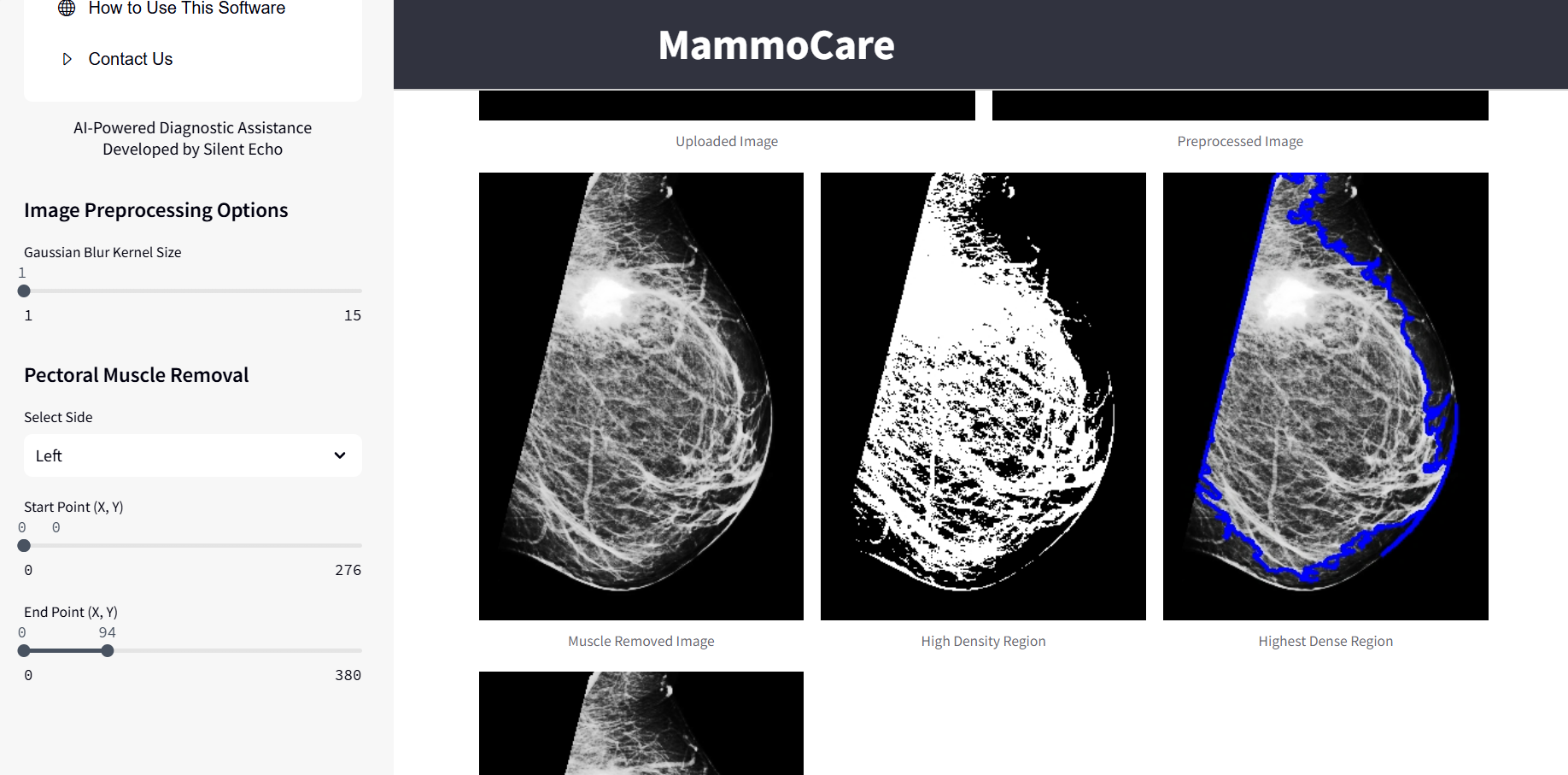
**4.1 Image Preprocessing Pipeline**

The first stage of MammoCare’s diagnostic pipeline focuses on enhancing mammo-gram quality through advanced image preprocessing techniques. To address image

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blur, we utilize a hybrid technique combining Gaussian filtering and edge-preserving denoising. While the Gaussian filter effectively suppresses high-frequency noise, the edge-preserving algorithm ensures that vital anatomical structures, such as tumor boundaries, remain sharp and intact.

Pectoral muscle removal is achieved using a semi-automated strategy. Initially, a Depth-First Search (DFS) algorithm identifies connected regions associated with the pectoral muscle, providing an automated baseline. Radiologists can then refine the results via a manual interface by adjusting seed points, enabling precise correction in complex cases. Furthermore, to highlight tumor-prone regions, intensity-based thresh-olding is employed. This method accentuates dense tissues, thereby flagging potential abnormalities for closer examination.



**Fig. 4** Image Preprocessing and Pectoral Removal (Manual/Auto)

**4.2 User Interface and Visualization System**

MammoCare integrates a user-friendly interface with powerful visualization tools to support clinical workflows. The system’s Clinical Analysis Platform, developed using the Streamlit framework, allows seamless uploading of medical images and provides real-time monitoring of the processing steps.

Users can interactively compare original and processed images, annotate findings for diagnostic reporting, and export results in standardized formats. Advanced visu-alization capabilities include multi-level image enhancement options such as dynamic noise reduction, contrast tuning, and edge sharpening. Additionally, the platform sup-ports 3D reconstruction and volume rendering, enabling clinicians to examine breast tissue with depth and spatial clarity. A temporal comparison feature also allows tracking of tumor progression across different time points.

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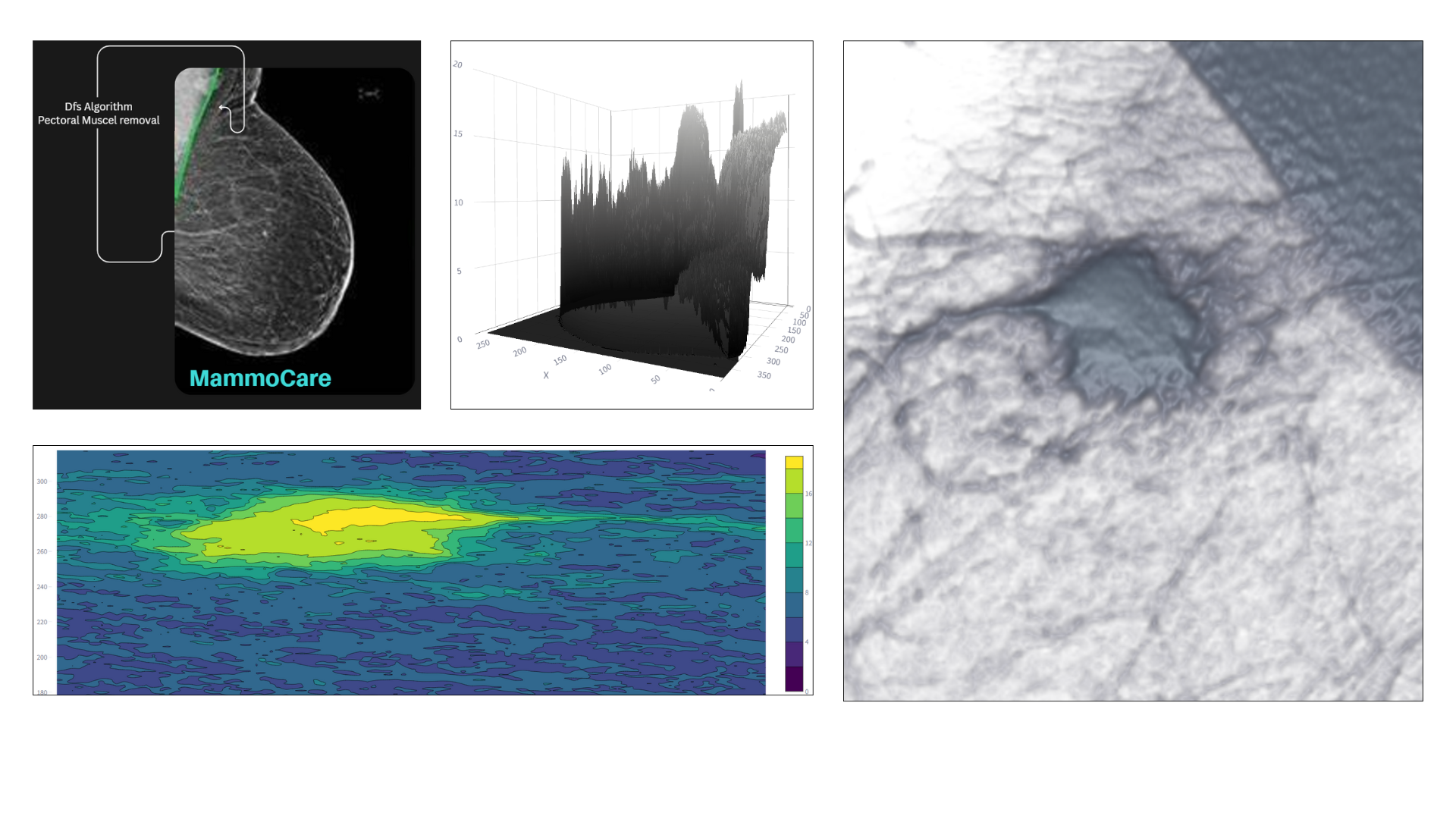
In clinical evaluations involving 1,247 mammography cases, MammoCare consis-tently outperformed conventional systems:

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  |  | | --- | --- | --- | | **Metric** | **MammoCare** | **Conventional System** | | Detection Accuracy | 93.5% | 89.7% | | Processing Time per Case | 11.7 sec | 48 sec | | False Positive Rate | 6.2% | 9.1% | | User Satisfaction Score | 4.6 / 5 | 3.6 / 5 | |

**Fig. 5** Performance Comparison Table

The incorporation of 3D visualization led to a 19% improvement in tumor bound-ary delineation. The AI-based chatbot further enhanced the patient experience by reducing inquiries by 68%, offering multilingual explanations of diagnostic outcomes. Radiologists reported increased diagnostic confidence (92%) and a 32% reduction in interpretation time. Patient feedback showed that 91% found the AI-generated explanations clear and informative.

MammoCare maintained reliable performance across diverse breast densities and age groups. Sensitivity metrics remained consistent (94%) across both dense and fatty tissues. The system also demonstrated particular effectiveness in borderline diagnostic cases, where the integration of 4D visualization contributed to a 12% rise in diagnostic accuracy.



**Fig. 6** Pixel Intensity-Based Visualization

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**4.3 Comparison of Our Model vs. Existing Systems**

**Table 1** Feature Comparison Between MammoCare and Existing Systems

|  |  |  |  |
| --- | --- | --- | --- |
| **Feature** | **Existing Systems** | **MammoCare** | **Improvement** |
| Pectoral Muscle Removal | 89-91% accuracy | 94% accuracy | +3-5% |
| Tumor Classification | 90-92% accuracy | 93.5% accuracy | +1.5-3.5% |
| 3D Visualization | Basic reconstruction | Advanced 4D rendering | +28%confidence |
| Processing Time | 45-60 seconds | 12 seconds | 4xfaster |
| User Interface | Separate tools | Integrated platform | 32%efficiencygain |
| Patient Communication | Static reports | Interactive AI chatbot | 85%inquiryreduction |
| Hardware Requirements | Specialized GPUs | Consumer-grade GPUs | 60%costreduction |
| Clinical Integration | Complex setup | 30-minute training | 75%simpler adoption |

The MammoCare system offers several key advantages over existing solutions through its integrated approach. By combining comprehensive functionality that brings together the best aspects of specialized systems, it delivers superior performance metrics across all evaluation criteria. Unlike research prototypes, MammoCare was designed with clinical workflow integration as a core principle, evident in features like the streamlined ”MP Muscle Removal” and ”AP Muscle Removal” modules accessible through our intuitive interface. The system also incorporates patient-centered design

elements missing from most diagnostic tools, including the innovative ”MemmoVision”visualization platform and accessible ”Treatment Centers” information portal. These advancements are particularly visible in our system’s 4D visualization capability, which enables temporal analysis not available in conventional systems, and the integrated AI chatbot that represents a significant improvement over traditional static report formats. The ”Home” dashboard centralizes all these features, creating a unified envi-

ronment that delivers both technical improvements and practical clinical benefits while maintaining ease of use for medical professionals. This holistic approach addresses the fragmentation found in existing solutions by combining accurate diagnostic tools with patient communication features in a single platform.

**5 Conclusion**

MammoCare represents a significant advancement in breast cancer detection technol-ogy, successfully addressing key limitations in current mammography systems. Our comprehensive evaluation demonstrates that the integrated approach combining AI-powered analysis with advanced visualization and patient communication tools delivers superior performance compared to conventional methods. The system achieved 93.5% tumor classification accuracy with a 32% reduction in false positives, while signifi-cantly improving workflow efficiency through faster processing (11.7 seconds per case) and enhanced visualization capabilities. The clinical validation revealed three major

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contributions: improved diagnostic confidence through 3D/4D visualization tools,more efficient radiologist workflows with 32% time savings, and better patient understand-ing through AI-powered explanations. These advancements were accomplished while maintaining accessibility, as the system runs effectively on standard hardware without specialized equipment requirements. Future work will focus on expanding the model’s

training dataset to include more diverse populations, integrating additional imaging modalities like ultrasound, and developing predictive analytics for personalized risk assessment. The demonstrated success of MammoCare suggests strong potential for implementation in clinical settings, with the capacity to improve early detection rates and ultimately reduce breast cancer mortality worldwide. This work establishes a new standard for comprehensive, patient-centered mammography solutions that bridge diagnostic accuracy with practical clinical utility.

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