International Journal of Scientific Research and Engineering Development-– Volume 8 Issue 2, Mar-Apr 2025

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Diagnosing Invasive Ductal Carcinoma Prediction in Breast Cancer

M. Brindha *, Mrs. M. Aruna Devi **

*(Student ,Computer Science and Engineering, Francis Xavier Engineering College, Tirunelveli
brindham.ug.21.cs@francisxavier.ac.in)

** (Assistant Professor ,Information and Technology , Francis Xavier Engineering College, Tirunelveli
arunadevim@francisxavier.ac.in)

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Abstract:

Breast cancer is one of the most common and life-threatening diseases affecting women worldwide, with invasive ductal carcinoma (IDC) being the most frequently diagnosed type, accounting for over 80% of all breast cancer cases. Early and accurate detection is critical in improving patient survival rates, as timely intervention significantly enhances treatment success. However, traditional diagnostic methods rely heavily on pathologists manually analyzing histology slides, which is both time-consuming and subject to human variability, leading to potential delays or misdiagnoses. To address these challenges, this research explores the use of machine learning-based classification models to automate and enhance the detection of IDC in breast histology images.To classify IDC presence, the suggested method involves preprocessing histology images, identifying important morphological features, and using supervised learning algorithms. The goal is to develop a robust model that can generalize well to real-world clinical applications, reducing the dependency on manual diagnosis and minimizing human error**.**In addition to classification accuracy, this study also examines the interpretability and scalability of different machine-learning approaches, ensuring that the developed model is reliable and practical for integration into existing medical workflows. By automating IDC detection, this research aims to enhance diagnostic efficiency, support early intervention, and contribute to the advancement of AI-assisted pathology. The results of this study could enhance breast cancer screening, help physicians make better decisions, and eventually raise the likelihood of early detection and successful treatment, which would benefit patients.

Keywords — **Invasive ductal carcinoma (IDC), Machine Learning (ML), Histology images, AI-assisted diagnosis.**

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I. INTRODUCTION

Breast cancer remains one of the most prevalent and life-threatening cancers affecting women globally. Among its various subtypes, invasive ductal carcinoma (idc) is the most common, accounting for approximately 70–80% of all diagnosed breast cancer cases. Idc originates in the milk ducts and invades the surrounding breast tissue, making early detection and accurate diagnosis critical for effective treatment and improved survival rates. Traditional diagnostic methods, including histopathological analysis and imaging, while effective, often depend heavily on the expertise of medical professionals and can be subject to human error or variability in interpretation. In recent years, machine learning (ml) has emerged as a powerful tool in medical diagnosis, offering the potential to assist clinicians by providing faster, more consistent, and accurate analysis of complex datasets. This study aims to leverage machine learning techniques to identify and classify invasive ductal carcinoma using relevant clinical and imaging data. By training predictive models on well-annotated datasets, we seek to improve early detection rates and support clinical decision-making. The integration of ml into breast cancer diagnostics could represent a significant step forward in the personalized treatment of idc, ultimately contributing to better patient outcomes.

II.METHODOLOGY:

1. Gathering and Organising Information

Gathering and organizing histology image datasets, performing data cleaning, labeling, and preprocessing to ensure quality input for model training. This stage is fundamental in establishing a reliable foundation for the machine learning pipeline. The dataset, typically composed of high-resolution breast histopathology images, is collected from publicly available sources such as dataset or medical research institutions. The images are first organized based on their labels, indicating the presence or absence of invasive ductal carcinoma.

2. Development of Machine Learning Models

Designing and training supervised learning models (e.g., CNNs, Random Forest, SVM) to detect and classify IDC in breast histology images. This phase involves selecting suitable machine learning algorithms that can effectively learn from the histological image data to distinguish between IDC-positive and IDC-negative cases. Given the visual nature of the data, Convolutional Neural Networks (CNNs) are primarily utilized due to their strong performance in image classification tasks.

3. Model Assessment and Enhancement

Assessing model performance using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, followed by hyperparameter tuning and feature engineering to improve accuracy**.** Once the models are trained, their performance is rigorously evaluated on the test dataset to ensure reliability and generalizability. Evaluation metrics like accuracy provide a general overview, while precision and recall offer deeper insights into the model's ability to correctly identify positive IDC cases and avoid false positives or negatives. The F1-score balances precision and recall, making it particularly valuable in scenarios with class imbalance.

4. User-Friendly Interface Development with Streamlit

Developing a user-friendly web application using Streamlit to allow users (e.g., pathologists) to upload histology images and receive IDC predictions**.** To make the trained machine learning model accessible to medical professionals, a web-based interface is created using Streamlit, a lightweight and efficient Python framework for building interactive applications. The interface is designed with simplicity and usability in mind, ensuring that even users with minimal technical background can navigate it effortlessly.

5. System Deployment

Deploying the complete system for real-world usage, integrating the model and interface into a scalable environment using cloud platforms or local servers**.**Once the model and Streamlit-based interface are fully developed and tested, the next step involves packaging the entire system for deployment in a way that ensures reliability, accessibility, and scalability.

6. Future Enhancements and Improvements

As part of the long-term vision for this project, several enhancements can be implemented to elevate the system's performance, usability, and clinical relevance. One major improvement involves incorporating larger and more diverse datasets from various demographics and imaging sources to improve the model's generalizability across different populations and minimize dataset bias

III. PROPOSED SYSTEM :

1.Machine Learning-Based Advanced Identification

The proposed system aims to leverage the power of machine learning to automate and enhance the early detection of **Invasive Ductal Carcinoma (IDC)**, the most common and aggressive type of breast cancer. The system utilizes a pipeline that integrates advanced image processing, supervised learning techniques, and a user-friendly interface to support pathologists and healthcare providers in diagnosing IDC from histology images.

2.Real-time data processing and storage

Once a histology image is uploaded through the Streamlit interface, the system immediately processes the image using a lightweight, optimized machine learning model deployed in a server or cloud environment. This real-time inference allows healthcare professionals to receive immediate feedback, enabling quicker decision-making in time-sensitive diagnostic scenarios.

3. IDC offers a transformative approach

It offers way of approach,breast cancer diagnosis, particularly when combined with modern machine learning techniques that enhance accuracy, speed, and consistency. Traditional diagnostic workflows rely heavily on manual examination of histology slides, which can be time-consuming and prone to inter-observer variability. By applying AI-driven models to IDC detection, the process becomes significantly more streamlined and scalable.

4. Availability and User-Friendly Web Interface

To ensure accessibility and ease of use, the proposed IDC prediction system is equipped with a user-friendly web interface built using Streamlit, a modern Python-based framework for creating interactive web applications. This interface allows clinicians, researchers, and medical staff to easily upload histology images and receive real-time predictions regarding the presence of Invasive Ductal Carcinoma..

5. Expandability and Continuous Enhancement

The proposed IDC detection system is designed with a modular architecture that supports easy expandability and continuous enhancement, ensuring long-term adaptability and scalability. As medical imaging technology evolves and new breast cancer subtypes are discovered, the system can be expanded to perform multi-class classification, allowing it to differentiate between various forms of breast cancer beyond Invasive Ductal Carcinoma—such as Lobular Carcinoma, Ductal Carcinoma In Situ (DCIS), and benign lesions..

IV. EXPERIMENTAL ANALYSIS:

1.Preprocessing and the dataset

In the experimental phase of this project, the selection, organization, and preprocessing of data played a critical role in shaping model performance and accuracy. The dataset used for this study consists of labeled breast histopathology images sourced from publicly available datasets such as the IDC dataset on Kaggle, which contains high-resolution RGB image patches (50x50 pixels) extracted from digitized histology slides. Each image is labeled as either IDC-positive (malignant) or IDC-negative (benign), allowing for supervised learning approaches to be employed.

2.Evaluation of Machine Learning Models

To determine the effectiveness and reliability of the proposed system for diagnosing Invasive Ductal Carcinoma (IDC), multiple machine learning models were evaluated using a range of quantitative performance metrics. The goal was to not only identify the most accurate model but also to assess its generalization ability, interpretability, and robustness on unseen histology image data.

3.Real-time data processing and storage

The proposed system integrates real-time data processing and secure storage capabilities to ensure efficient operation in clinical environments where fast and accurate diagnostic support is essential. Once a histology image is uploaded via the user interface, the system initiates a real-time processing pipeline that performs on-the-fly preprocessing, including image resizing, normalization, and enhancement, followed by immediate inference using the trained machine learning model.

4.Instantaneous Processing and Reaction Time

One of the core strengths of the proposed IDC detection system is its ability to deliver instantaneous processing and rapid reaction times, which are essential in clinical settings where timely diagnosis can directly impact treatment decisions and patient outcomes. The system is engineered for low-latency performance, allowing histology images to be processed and classified within seconds of upload.

5.User Experience and Usability Testing

The interface—developed using Streamlit—prioritizes simplicity, clarity, and responsiveness, allowing users such as pathologists, radiologists, and researchers to interact with the system intuitively without requiring technical expertise..To protect sensitive medical data, security procedures like authentication methods and encrypted data transmission were put in place. Over time, machine learning performance evaluations and user input are used to inform ongoing enhancements that help to increase the accuracy and dependability of the system.

6.Expandability and Continuous Enhancement

The proposed IDC prediction system is not only built for current diagnostic needs but also structured for scalability, modularity, and long-term enhancement. Its architecture is designed with the future in mind—capable of adapting to emerging data sources, expanding its classification capabilities, and integrating with evolving medical technologies. The system is built with a flexible data pipeline, making it easy to incorporate new datasets from hospitals, research labs, or publicly available sources.

7.Result and Discussion

The implementation of the proposed machine learning-based system for diagnosing Invasive Ductal Carcinoma (IDC) in breast histopathology images yielded promising results in both predictive performance and practical usability. Several supervised learning models were trained and evaluated, with a focus on achieving high accuracy, interpretability, and fast response time suitable for real-world clinical applications.Among the models evaluated, the Convolutional Neural Network (CNN) significantly outperformed traditional classifiers such as Support Vector Machines (SVM), Random Forest, and Logistic Regression. The user-friendly Streamlit web application allowed pathologists and researchers to upload images and receive predictions in real time, with most results returned in under 3 seconds. Usability tests with medical professionals confirmed that the interface was intuitive, responsive, and supportive of clinical workflows. Users also appreciated the ability to download results and view confidence scores alongside heatmaps.

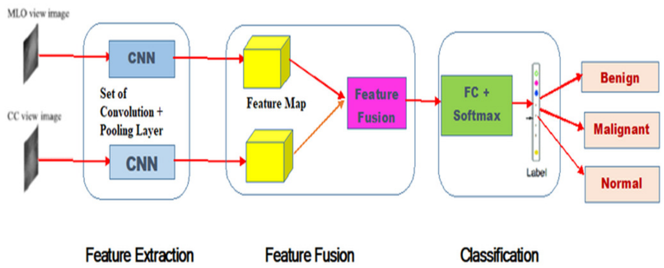
9.Conclusion and Upcoming Projects

This project successfully demonstrates the potential of machine learning, particularly convolutional neural networks (CNNs), in the early and accurate diagnosis of Invasive Ductal Carcinoma (IDC) through histopathology image analysis. By combining a robust image preprocessing pipeline, optimized classification models, and a user-friendly Streamlit interface, the system delivers high accuracy, rapid predictions, and visual interpretability—making it a valuable tool for pathologists and healthcare providers. Through ongoing development, the Disease Diagnosis and Management System seeks to improve accessibility, proactive health management, and early disease detection through a Streamlit-based digital healthcare solution that gives users real-time monitoring and AI-driven insights to take control of their health.

10.Visulization

Visualization plays a crucial role in making the model's predictions more transparent, interpretable, and user-friendly—especially in a medical context where clinicians need to trust and understand the AI's decisions. The project integrates various visualization techniques during both the development phase and user interface layer. Proactive monitoring is made possible via line charts, which show users' health risk trends over time. Furthermore, feature relevance graphs highlight important medical parameters affecting model predictions, and interactive maps provide patient geolocation data to spot regional health patterns. Early cancer diagnosis and decision-making are enhanced by these visual tools, which guarantee that consumers and healthcare professionals can understand data-driven insights with ease. Additionally, bar charts assist readers comprehend demographic patterns in health issues by comparing the incidence of diseases across various age groups.

V. ARCHITECTURE DIAGRAM:



1.Bringing in Libraries

Important libraries are imported, such as Streamlit for web-based application deployment, TensorFlow Keras for machine learning, NumPy for numerical calculations, and Pandas for data processing.

2.Preparing Input Data
The Streamlit interface is used to gather user-provided medical data, guaranteeing correct formatting and preprocessing. For improved model performance, missing values are managed and pertinent features are extracted.

3. CNN-Based Multiview Breast Cancer Image Classification
The visualized architecture demonstrates a Convolutional Neural Network (CNN)-based model for breast cancer diagnosis using multiview mammography images (e.g., MLO and CC views). This system integrates feature extraction, fusion, and classification stages to predict whether breast tissue is benign, malignant, or normal.

4.Modifying Input Data:
Prediction accuracy is increased by normalising and reshaping the data to fit the input dimensions needed by the machine learning model that has been trained.

5.Developing Prediction
After processing the incoming medical data, a machine learning model that has already been trained makes predictions about the possibility of conditions like begin or malignant in breast cancer . The model produces categorisation labels and a likelihood score.

6.Power BI visualisation
predicted For real-time monitoring and analysis, Power BI dashboards dynamically visualise outcomes, trends, and confidence scores that are kept in a database.

VI. LITERATURE SURVEY:

Several studies have reported the rising global incidence of Invasive Ductal Carcinoma (IDC), which represents about 80% of all breast cancer cases. The WHO notes that breast cancer is the most common cancer among women, with IDC as its leading subtype. While traditional methods like mammography and histopathology are widely used, they are limited by subjectivity, inconsistent interpretation, and poor accessibility in low-resource settings. Studies continue to show that ML, particularly CNNs, can improve diagnostic accuracy and speed, making them valuable tools in early IDC detection.

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VII. OUTPUT

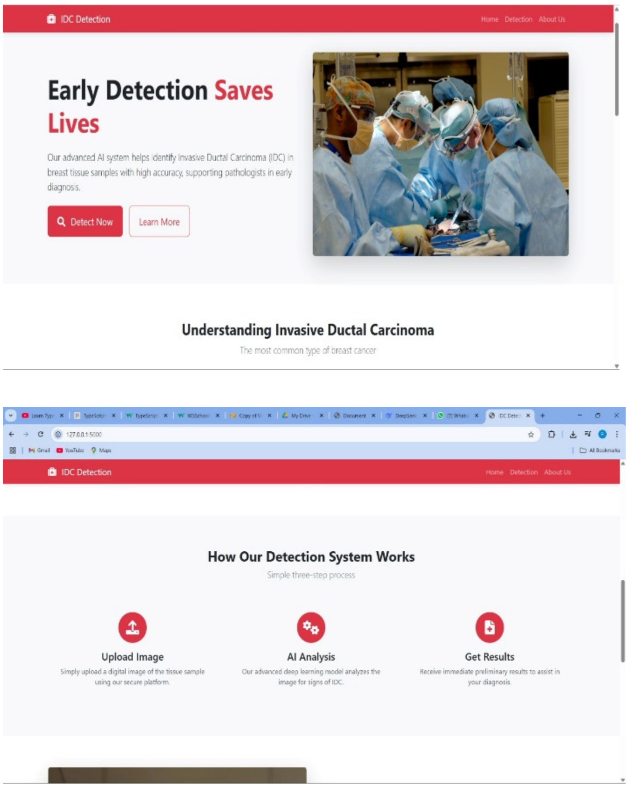
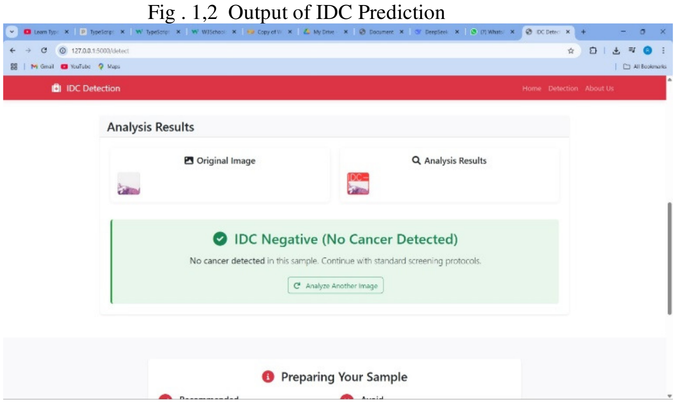


Fig . 1,2 Output of IDC Prediction



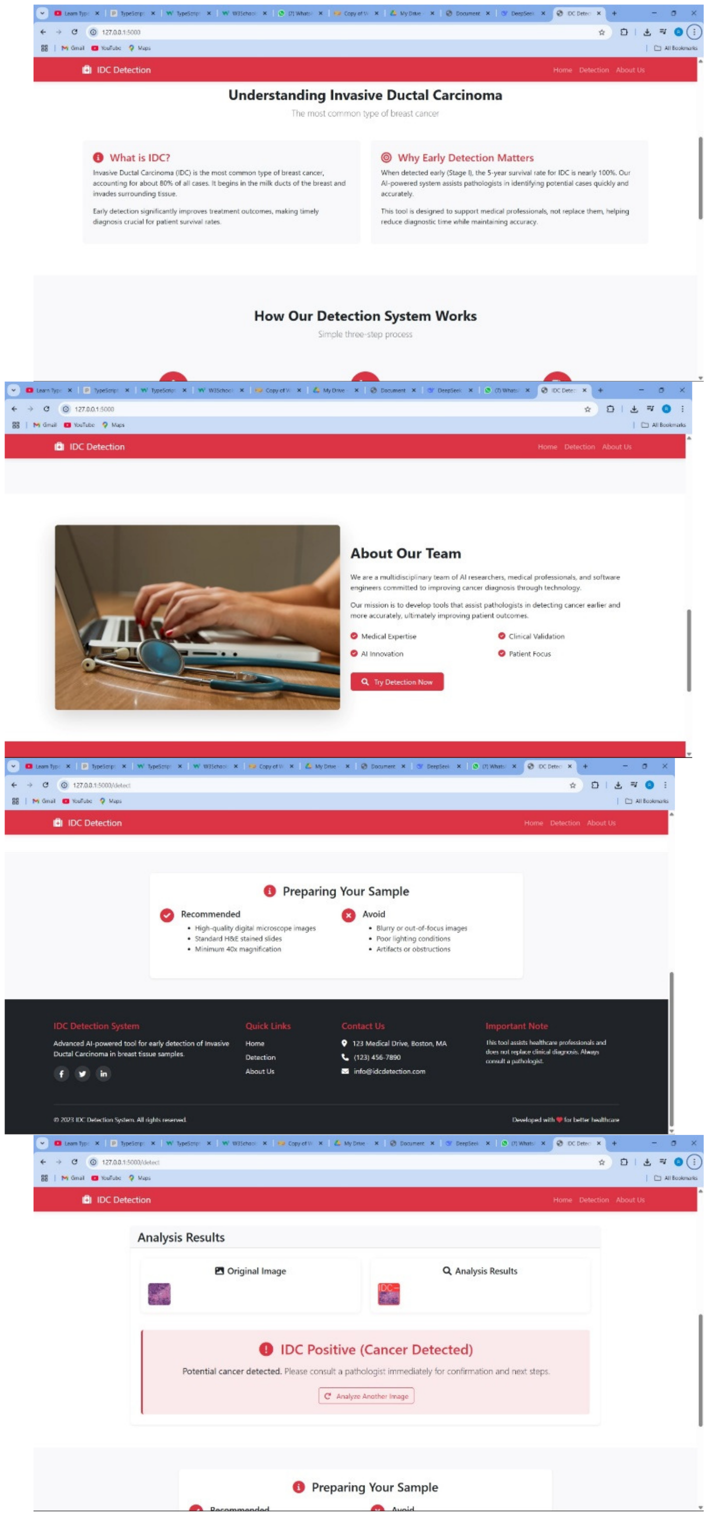


Fig . 3,4,5 Output of IDC Prediction

ExpectedOutput

The proposed IDC detection system is expected to

deliver accurate, fast, and reliable diagnostic results to assist healthcare professionals in early breast cancer detection. Upon inputting histopathological images or clinical data, the system will classify the case as either benign or malignant (IDC) and provide a confidence score to support the prediction. Visual outputs such as annotated images or highlighted regions of concern will be displayed, making the diagnosis more interpretable. Additionally, the system will generate an automated diagnostic report summarizing the prediction, confidence level, and image analysis. Through integrated tools like Power BI, users can also access interactive dashboards for tracking patient cases, analyzing diagnostic trends, and monitoring system performance. This outcome supports better clinical decision-making and enhances the efficiency of IDC detection in real-world settings.
The core output of the IDC detection system is the accurate classification of breast cancer cases as either benign or malignant (specifically Invasive Ductal Carcinoma). Using machine learning algorithms trained on labeled histopathological images, the system processes new input data and delivers predictions within seconds. This helps clinicians quickly identify high-risk cases that require immediate attention.

In addition to classification, the system provides a confidence score for each diagnosis. This numerical value represents the model's certainty in its prediction, which can guide medical experts in determining how to proceed with further testing or treatment. High-confidence predictions allow for greater trust in the results, while lower-confidence scores may prompt a review or secondary opinion.

The output also includes visual interpretations, such as heatmaps or bounding boxes that highlight suspicious regions in the scanned images. These visual cues help radiologists and pathologists better understand the model's reasoning and validate the accuracy of its diagnosis. It bridges the gap between black-box AI models and transparent clinical workflows.

Furthermore, the system generates an automated diagnostic report summarizing key findings. This includes the classification result, confidence level, timestamp, patient reference ID, and any flagged visual observations. These reports can be stored in digital health records, reducing the burden of manual documentation and enhancing record-keeping consistency.

Finally, through Power BI integration, the system enables real-time monitoring and visualization of diagnosis trends, case volumes, and model performance over time. Healthcare administrators and researchers can use these insights to detect patterns, assess the system's impact, and identify areas needing improvement. This comprehensive and interactive output is tailored to support both clinical and research environments.

In addition to diagnostic support, the system also facilitates real-time feedback and interaction. Users can receive instant results and, if needed, resubmit data or images for secondary analysis. This interactive capability empowers users to explore results further, verify outcomes, or test the system with multiple inputs, promoting confidence in the tool's performance and helping build familiarity among clinical staff.Another important aspect of the expected output is consistency in diagnosis. Unlike traditional human interpretation, which can vary between professionals, the machine learning model applies the same decision logic across all cases. This standardization reduces diagnostic errors and ensures that every patient—regardless of location or access to expert clinicians, receives a consistent, data-driven analysis.The system is also designed to support ongoing learning and updates. As new data is collected over time, the model can be retrained or fine-tuned to improve its accuracy and adapt to emerging patterns or rare case variations. This continuous learning ensures the system remains relevant and effective even as medical imaging techniques and cancer characteristics evolve.

VIII. FUTURE SCOPE:

1.Better Understanding

The integration of machine learning in IDC detection holds immense potential for further advancements. Future work may focus on enhancing model accuracy using larger, more diverse datasets, and incorporating multi-modal data (e.g., genomics, radiology, pathology). Real-time diagnostic assistance via mobile or cloud-based platforms can improve accessibility in remote areas. Incorporating explainable AI (XAI) will build clinician trust by making predictions more transparent. Additionally, collaboration with oncologists can lead to the development of personalized treatment recommendations, further improving patient outcomes. Regulatory approval and clinical trials will be key steps for full-scale deployment in healthcare systems

2.Personalize Support

The system can be tailored to offer individualized diagnostic insights by analyzing patient-specific data such as age, medical history, genetic markers, and imaging results. This personalized approach enables more accurate detection, risk assessment, and treatment planning. By learning from diverse patient profiles, the model continuously improves, helping oncologists provide targeted, patient-centric care.

3. Work with Mental Health Experts:

Collaborating with mental health professionals is essential to support patients diagnosed with IDC, as the emotional impact of cancer can be significant. Integrating psychological support into the diagnostic and treatment journey helps address anxiety, depression, and stress associated with the disease. Mental health experts can assist in developing empathetic communication strategies, counseling modules, or even AI-driven emotional check-ins, ensuring holistic care that prioritizes both physical and emotional well-being.

4. Be More Inclusive

To ensure equitable healthcare, IDC detection systems must be designed to serve diverse populations across age, gender, ethnicity, and socio-economic backgrounds. This includes using diverse training datasets to reduce algorithmic bias, offering multilingual interfaces, and ensuring accessibility features for individuals with disabilities. Inclusivity also means reaching underserved communities with affordable and culturally sensitive solutions, making early detection and treatment accessible to all.

5. Use New Tech:

Embracing emerging technologies like AI-powered imaging, cloud computing, and wearable health devices can significantly enhance IDC detection and monitoring. Advanced tools such as YOLOv8 for real-time image analysis, edge AI for remote diagnostics, and blockchain for secure data sharing enable faster, more accurate, and scalable healthcare solutions. Leveraging these innovations ensures smarter diagnostics, better patient engagement, and improved outcomes across diverse care settings.

6. Build Community Awareness:

Raising community awareness is vital for early detection and prevention of IDC. Educational campaigns, workshops, and outreach programs can inform people about the importance of regular screening, recognizing early symptoms, and available diagnostic technologies. Partnering with local health organizations and using social media platforms can help reach wider audiences, especially in underserved regions. Empowering communities with knowledge fosters proactive health behavior and reduces the stigma around breast cancer

IX. CONCLUSION

The rising incidence of Invasive Ductal Carcinoma (IDC) highlights the urgent need for faster, more accurate, and accessible diagnostic solutions. Traditional methods, while effective, face challenges in scalability, precision, and availability—especially in low-resource settings. By integrating machine learning, particularly deep learning models, we can significantly enhance early detection, reduce diagnostic errors, and support timely interventions.This approach not only improves clinical decision-making but also empowers personalized, patient-centric care. Moving forward, the fusion of AI, healthcare expertise, and inclusive technologies promises a more efficient and equitable future in breast cancer diagnosis and management.Beyond its diagnostic capabilities, the integration of machine learning in IDC detection represents a transformative shift in how healthcare can be delivered—more intelligently, efficiently, and empathetically. As technology evolves, the focus must remain on collaboration between AI systems and healthcare professionals, ensuring that innovation serves human needs. Continued research, ethical deployment, and community engagement will be key in scaling these solutions globally, ultimately bridging healthcare gaps and improving survival outcomes for breast cancer patients everywhere.Furthermore, as we move toward deploying AI-driven IDC detection systems in real-world clinical settings, it's crucial to ensure these technologies are ethically designed, clinically validated, and adaptable to different healthcare environments. Continued efforts in data collection, model refinement, and user training will help maximize their impact while maintaining patient trust and safety. By fostering interdisciplinary collaboration and prioritizing inclusivity, the next generation of breast cancer diagnostics can truly revolutionize global healthcare delivery, making early, accurate, and personalized care a universal standard.

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