

Ultrasound Image Analysis for Breast Cancer Detection and Prognosis Prediction Using DL

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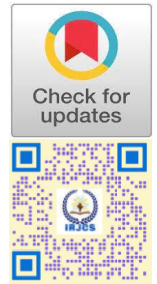
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Publication History

Manuscript Reference: IRJCS/RS/Vol.13/Issue01/CSJA26.JACS10086

Research Article | Open Access | Double-Blind Peer Reviewed Article ID: IRJCS/RS/Vol.13/Issue01/CSJA26.JACS10086

Received:12,December 2025,Revised:24,December 2025,Accepted:02 January 2026 Published Online:20 January 2026

<https://www.irjcs.com/volumes/Vol13/iss-01/07.CSJA26.JACS10086.pdf>

Article Citation:Shwetha,Pravallika,Navyashree,Varshitha,Poojitha(2026),Ultrasound Image Analysis for Breast Cancer Detection and Prognosis Prediction Using DL, IRJCS: International Research Journal of Computer Science, Volume 13, Issue 01 of 2026 pages 33-36

Doi-> <https://doi.org/10.26562/irjcs.2026.v1301.07>

BibTeX Key Shwetha@2026Ultrasound

IRJCS papers should be cited as IRJCS (International Research Journal of Computer Science, AM Publications, India 2026, ISSN 2393-9842, <https://doi.org/10.26562/irjcs.2025.v1301.07> The journal's official abbreviation is IRJCS.

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Abstract: Breast cancer still claims thousands of lives each year. Early detection? It's a lifesaver, period. We've created a two-component system that processes ultrasound images and, at the same time, processes clinical information to not only identify cancerous tissues, but to also determine potential progression. Here's the process: Component one uses a VGG19 neural network to scan ultrasound images of the breasts, separating them into normal tissues, benign, and cancerous tissues. Component two processes clinical data, including the patient's age, tumor type, and medical history, to determine the potential aggressiveness and progression of the cancer through machine learning. It all happens through a web app interface. Python supports the calculations. Meanwhile, the interface itself uses HTML and CSS. We get a system that integrates image analysis and data analysis for clinical purposes, not requiring expertise to operate and interpret results.

Keywords: Breast cancer detection, Ultrasound classification, Deep learning, VGG19 architecture, Clinical data analysis, Disease progression prediction.

I. INTRODUCTION

The number of breast cancer cases is rising rapidly each year. Simply put, the sooner pathologies are identified, the better chances of successful treatment. This is where ultrasound technology, now the imaging technique of choice for doctors, comes into the picture. It's hard to beat the advantages that ultrasound imaging offers: non-ionizing radiation, budget-friendly, and irrespective of the density of the breast tissue. But this technique offers one major problem. It requires physicians to interpret the images. This process takes time. Lots of time. Additionally, the results are not standardized, and this holds especially when those images are marred by acoustic noise and today, the process of breast cancer detection via ultrasound has several limitations. In most hospitals, radiologists can only manually analyze images. Tedious? Yes. Inconsistent? Yes.

Even for experts, analyzing images with distractions, such as lack of contrast, and subtle differences between benign and malignant tissues can be challenging. As a result, diagnoses may be inconsistent; that is, two radiologists may arrive at two different diagnoses from the same images. By adding to this the number of screenings is steadily rising, causing greater mental stress for medical personnel. Traditional AI attempts to use handmade extraction features lack contrast. This is where deep learning plays an important role. CNNs are proven state-of-the-art performers when used for medical imaging. They pick out features that might not be immediately visible to the human eye. Patterns and features may include things like texture patterns, small boundary distortions, and regional differences in brightness. Simultaneously, the specific characteristics and needs of the actual patient, including their age, genetic patterns, and the actual size of the tumor, are invaluable to physicians when diagnosing the path that the disease might take approaches? You receive a more comprehensive view of support in both early diagnosis and long-term predictions. This is what our system does exactly! We literally integrated classification using ultrasound techniques and data-driven predictions using a single system of prognosis for cases of breast cancer.

II. PROBLEM STATEMENT

Current breast cancer diagnoses by ultrasound are plagued by several issues. Most hospitals are still depending on radiologists visual analysis of the ultrasound images. "Time consuming? Yes. In consistent? Yes." Of course, even experienced professionals will find it difficult to make clear diagnoses if the images are noisy, the contrast is low, or whether malignant or benign lesions are similar in appearance. This will lead to inconsistency in the results because "two radiologists interpreting the same image could possibly get different answers." And the demand for screening the number of patients keeps growing. But there is an even more important missing aspect. Current systems and solutions essentially evaluate the presence and type of cancer. However, there is also one more important gap that currently needs to be fulfilled. What today's systems currently do is to detect the presence of cancer and classify it according to type. However, they don't go any further than that. What they don't do is predict how that particular cancer will progress. Whether that cancer will be aggressive, or stable is not important as far as they are concerned. However, as important as cancer type is cancer prognosis, which is currently determined manually after analyzing many different parameters such as cancer size, lymph node status, hormone receptor status, age, and genetics. These essential factors significantly influence the treatment choice.

III. LITERATURE SURVEY

Ultrasound imaging dominates breast cancer evaluation for good reasons safety, affordability, effectiveness with dense tissue. Yet challenges persist. Grainy artifacts. Technician-dependent quality. These issues have pushed researchers toward automated deep learning solutions. Ciobotaru's team [1] explored boundary detection for tumor delineation. Their system showed promise but struggled maintaining consistency across varying scan quality. Zhang and colleagues [2] developed something they called a Structure-Aware Triplet Path Network, which improved lesion differentiation through reconstruction mechanisms and standardized feature correlations. Clever approach. Afrin's comprehensive study [3] examined deep learning across multiple ultrasound modes. The findings? These methods definitely advance lesion identification. But they hit walls small datasets, insufficient validation protocols. Common problems in medical AI research. The BI-RADS-Net system [4] tackled interpretability directly, linking cancer assessments with standardized clinical descriptors via multi-task learning. This matters because doctors need to understand why the AI reached its conclusion, not just what conclusion it reached. Maruf's work [5] combined radiomics with transfer learning, achieving better accuracy but demanding substantial computing power a practical deployment barrier. Bansal's research [6] demonstrated that compact CNN architectures could produce acceptable results while being less resource-intensive. Trade-off? Over fitting tendencies. Methods incorporating U-Net variants [7] and combined segmentation-classification workflows [8] showed strong performance in controlled studies. Still, clinical deployment remains limited due to dataset diversity challenges and generalization issues. All this research highlights deep learning's growing potential for breast ultrasound analysis while underscoring the ongoing need for reliable, clinically practical diagnostic systems that work across diverse patient populations and equipment setups.

IV. METHODOLOGY

Developed a module based system in which various predictive algorithms work through a common web interface. The Flask server is responsible for managing various modules for diagnostics, directing user queries to relevant models. There is flexibility in models supported the traditional machine learning models based on classifiers saved as pickle files and models based on H5 files supported by neural networks. Every model is contained within its own separate function to ensure visibility and autonomy. There is also a series of processes that the predictive model goes through the data acquisition, transformation, and standardization, model initialization, predictive computations, and explanation. If it is an image, the ultrasound images uploaded will be resized and scaled, mapped to convert to tensor space as required by the CNN model. It has a frontend where it displays the output of the model in formatted templates that contain feedback in words, as well as graphical displays of model confidence. Error handling has been incorporated in the system; it can notice errors such as missing data or the wrong type of files, giving feedback that is clear to the user. Such a multi-layered design implies that every module functions independently and simultaneously helps to provide a well-integrated diagnostic environment. The current approach includes the capability of employing a variety of prediction engines for breast problems, liver ailments, cardiovascular diseases, and pulmonary infections, thus proving the malleability of the proposed design.

V. SYSTEM ARCHITECTURE

The Fig.1, reflects the design of the ultrasonic image processing system, which also considers the factor of deduction and prognostication. The design of the ultrasonic image processing system also uses two separate process streams for image processing for diagnoses and medical information, and this aims at deducing and making prognostications regarding the growth and development of breast cancers. The design of the ultrasonic image processing system also relates to uploading images from ultra-sounds and the medical factor, which deals with the input parameter (age, tumor stages, medical history for parameters of a patient with cancer). The input parameters can also be directed towards the image processing sub-systems, and this comprises the process of standardization and equalization, resizing, and optimizing the input parameters for our design of models. The parameters can also be directed towards two separate process streams. Processing Stream One: The first process stream comprises a CNN and VGG19 model, which aims at deducing ultra-sound images classified under normal, benign, and ultra-sound images that are cancerous. Processing Stream Two: The second process stream comprises a Logistic Regression model, which aims at deducing the type that relates to the growth and development stages for the malignancy type, which refers to cancer, and this also includes classifying the type that relates to malignancy and categorized and can be described and defined under malignancy that is progressively divergent and non-divergent.

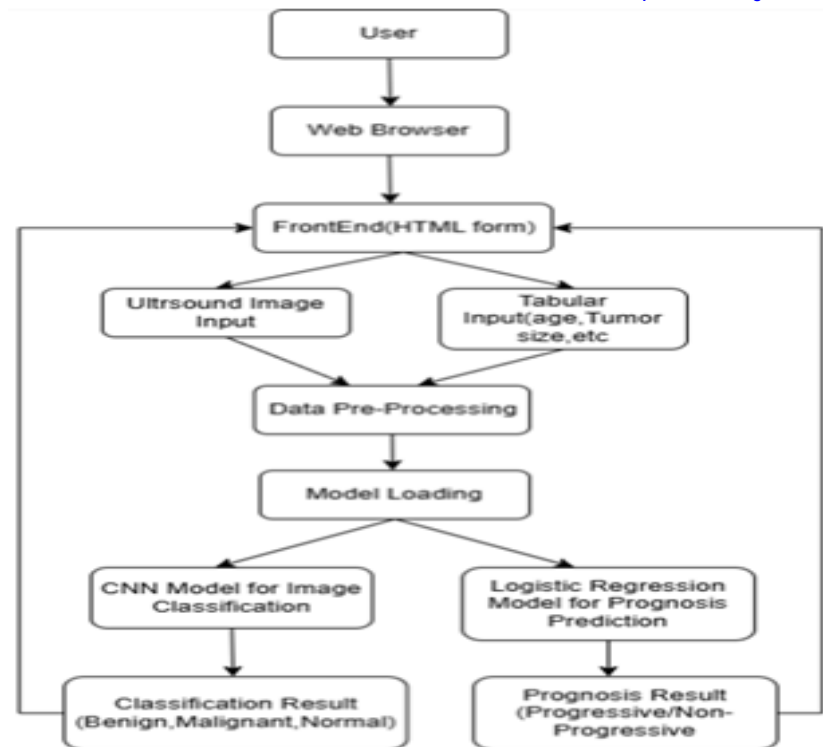


Fig 1: System Architecture

VI. DATAFLOW

Figure 2 shows the data flow architecture for our system. Our system has a twin pathway system for medical diagnostics in which tasks in our system are initiated by user inputs through two major pathways, namely the ultrasound image submission pathway and the clinical data input pathway. The ultrasound pathway: The images are preprocessed (removal of noise, image normalization, image resizing) before the images can undergo processing by the VGG19 convolution neural network classifier. The images can then be categorized as benign, malignant, or normal by the classifier. On the other hand, the clinical data stream handles patient data from the preprocessing techniques such as missing value treatment, feature encoding for the categorical attributes, and normalization for the numerical attributes. This is used as the input for the proposed ML model. The prognosis prediction results distinguish the non-progressive and progressive diseases. These two data streams operate simultaneously and complement each other. The ultrasound stream focuses heavily on the categorization of the instantaneous diagnosis. The clinical data stream focuses more on the evaluation of the prognostic predictive outcomes.

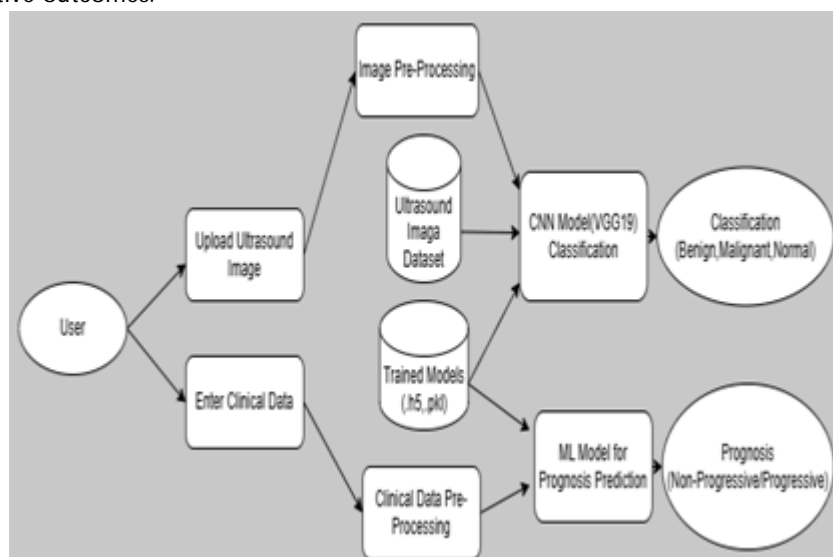


Fig 2: Data Flow

VII. RESULTS AND ANALYSIS

We tested our two-stage platform within a web-deployed environment combining real-time ultrasound classification with clinical prognosis forecasting. Results exceeded our initial expectations.

Stage 1: Image Classification

The advanced VGG19 model, trained using classified images from ultrasound scans, categorized into normal, benign, and malignant, has an accuracy of 85.70%. Users can upload the images from scans and get immediate results.

From tests involving several sample images, the model clearly possesses skill in classifying, even under conditions that can be noisy or change the structure often. The images produced clear results for classifying malignant, benign, and normal images. The created AI possesses skill in recognizing morphological characteristics, like boundaries and echo, and geometric characteristics.

Stage 2: Prognosis Prediction

According to sources, this stage investigates clinical attributes that influence the growth and stability of the tumor. Our Logistic Regression model attained an accuracy of 93.68 percentage, an impressive performance based on prognosis prediction. Users enter clinical information using the web system. The system generates predictions along with confidence levels. For example, in one example, the system reported the tumor as non-progressive with confidence at 96.21%. Another example reported tumor progression at 86.82% confidence.

User Interface Integration

The interface combines both steps into three major components: control panel, ultrasound classifier, and prognosis predictor. The design is also very easy to understand and interpret, both by medical and non-medical personnel. These findings therefore confirm the effectiveness of the approach that combines deep learning and the structured analysis of data for analyzing breast cancer.

VIII. CONCLUSION AND FUTURE WORK

This study proves an integrated approach for the evaluation of breast cancer, which incorporates the classification of the ultrasound images along with the prognosis prediction based on the clinical data analysis. Utilizing the VGG19-CNN for image analysis, along with the Logistic Regression for the analysis of the tabular data, our solution has both the capability for diagnosis as well as prognosis. As a web-based solution, our system improves the usability for the convenience of the medical professionals as well as the researchers. Future Enhancements: There exist several ways of improving this work. Adding a more complex neural architecture, such as Efficient Net or Attention-based, can provide higher performance accuracy. Merging all the preprocessing steps into a single module may also improve computational complexity. Adding interpretability techniques, such as Grad-CAM or SHAP, can also serve to facilitate a greater understanding of the results provided by clinicians and can improve acceptance. Adding functionality for other diseases, automating report writing, and improving interface components can also provide a boost. Upgrading the application deployment over cloud technology that includes safe and real-time processing authorizations will increase the flexibility and relevance of this application within all hospital scales, from large ones to small ones.

ACKNOWLEDGMENT

We express profound gratitude to our project supervisor, Prof.R.Shwetha, for unwavering support, valuable insights, and mentorship throughout this investigation. We also acknowledge the Department of Computer Science and Engineering, Vemana Institute of Technology, for the necessary infrastructure and facilities in rendering this work possible. We also acknowledge important tools and platforms used during model creation, dataset transformation, and performance evaluation. The team's cooperation and relentless dedication by all the members have given us considerable assistance in reproducing these results of research.

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