Deep Learning-Based FBG Smart Palpation for Accurate Breast Tumor Detection and Localization

V. Bharathi Devi[1], Mrs.H.S.Anuja[2]

[1]*PG Scholar Bio-Medical Department, Udaya School of engineering, Kanyakumari Tamil Nadu, India.*
[2]*Assistant Professor Bio-Medical Department, Udaya School of engineering, Kanyakumari, Tamil Nadu, India.*

Abstract-*Breast palpation has long been a key method for detecting abnormal lumps, like tumors, in early breast examinations. However, this traditional technique depends heavily on the experience of the physician and doesn't offer consistent, measurable results. To improve this, researchers have developed an innovative smart palpation system that combines advanced sensing technology with artificial intelligence. This new device uses Fiber Bragg Grating (FBG) sensors embedded in a soft, flexible probe that mimics the natural touch of a human hand. The probe gently presses into the breast tissue with controlled, precise movements, capturing detailed information about tissue stiffness at different depths. This provides a clearer and more accurate picture than conventional methods. The strain data gathered during palpation is translated into quantitative stiffness profiles, which are then analyzed by a deep learning model combining convolutional neural networks (CNN) with bidirectional long short-term memory (BiLSTM). This hybrid AI framework detects tumors and maps their location and size using a visual heatmap, giving clinician's valuable insights beyond simple detection. Tests with breast tissue models containing embedded inclusions demonstrated that the system works effectively under both controlled and freehand conditions. By integrating FBG sensing, soft robotics, and AI-driven analysis, this approach promises an objective, repeatable, and comfortable breast examination experience, representing a significant advance toward next-generation digital palpation tools.*

Key Words: Smart Palpation System, Fiber Bragg Grating (FBG), Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (BiLSTM).

1. INTRODUCTION

Breast cancer stands as one of the most common and dangerous diseases affecting women worldwide, making early detection essential to improving survival chances. Traditionally, doctors have relied on manual palpation feeling for abnormal lumps or tumors by hand. While this method has been a staple for many years, it depends heavily on the skill and experience of the physician, often lacking consistency and precise measurement [1]. Advances in medical technology have introduced imaging techniques like mammography, thermography, and MRI to aid diagnosis. These tools improve accuracy but come with drawbacks such as high costs, exposure to radiation, and limited availability, especially in certain regions [2], [6]. Recently, artificial intelligence (AI) and deep learning have opened new doors for breast cancer detection. Techniques like convolutional neural networks (CNNs) excel at analyzing medical images, identifying tumors with impressive accuracy [1], [4]. More sophisticated models combine CNNs with bidirectional long short-term memory (BiLSTM) networks to capture both spatial and sequential information, allowing not just detection but also detailed localization and characterization of tumors [5], [8]. These advances provide clinicians with richer, more actionable insights [7]. Despite impressive progress, most current methods still rely on images and don't replicate the crucial sense of touch that doctors use during physical exams. To bridge this gap, researchers are now integrating smart sensing technologies with AI. Innovations include sensor-embedded gloves and probes that detect lumps by measuring changes in pressure and tissue stiffness [9]. These tactile systems aim to deliver objective, repeatable measurements, improving upon the subjective nature of traditional palpation. Among these technologies, Fiber Bragg Grating (FBG) sensors show great promise. Known for their sensitivity and flexibility, FBG sensors can accurately measure strain and, when embedded in soft robotic probes, can mimic the gentle touch of a human hand. This allows them to assess tissue stiffness at various depths, gathering detailed data that deep learning models analyze to create stiffness profiles and visual heat maps [3], [10]. This combination enables precise tumor detection and pinpointing. In modern healthcare, the fusion of soft robotics with intelligent sensing is transforming how medical examinations are done. This innovative system allows for precise and consistent palpation, overcoming the inconsistencies that often arise from manual exams. What makes this technology particularly effective is its flexibility; it works seamlessly both under guided protocols and during freehand use, all while maintaining steady, reliable data collection. This adaptability ensures that the system performs well across various clinical settings, providing dependable results every time. By enhancing the accuracy and reproducibility of examinations, this approach not only supports healthcare professionals but also paves the way for more practical and trustworthy applications in everyday medical practice. In modern medical diagnostics, a new approach is making a significant difference. By relying on quantitative, data-driven results, this method helps reduce human errors and ensures more consistent diagnoses. Patients also benefit from the process, as the examinations are non-invasive and carefully controlled, which greatly enhances comfort during the procedure. Thanks to these improvements, this system is especially effective for early-stage detection and is well-suited for routine clinical screenings, offering a promising tool for better healthcare outcomes. In summary, blending FBG-based sensing, soft robotics, and AI-driven analysis marks a major leap forward in breast cancer screening. This innovative approach offers a non-invasive, reliable, and highly accurate alternative to traditional methods, enhancing early detection and ultimately improving outcomes for countless women.

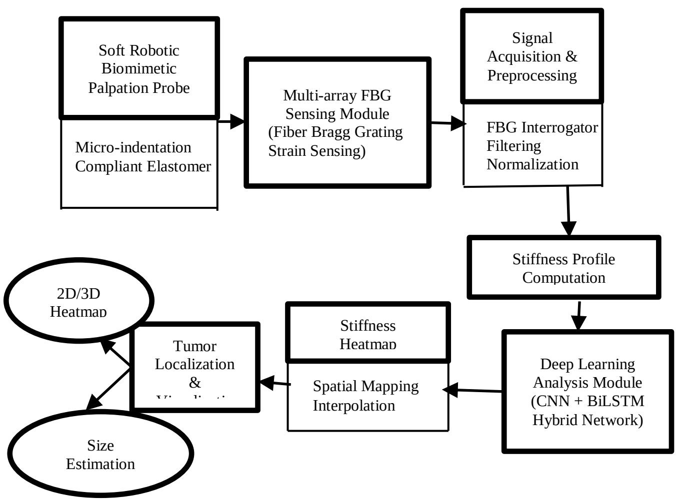

Fig 1: Architecture diagram

2. METHODOLOGIES

Early detection of breast cancer is crucial, yet traditional methods like manual palpation and ultrasound have their limitations. To address these challenges, a new smart tactile palpation system has been developed, combining soft robotics, advanced sensing, and artificial intelligence to offer a more objective and reliable way to detect breast tumors early. The heart of this system is a soft robotic probe designed to feel and behave much like a human hand. Its flexible, biomimetic structure adapts gently to different breast shapes and tissue stiffness, ensuring patient comfort and consistent examination. Embedded within the probe is a network of highly sensitive Fiber Bragg Grating (FBG) sensors that detect tiny changes in tissue pressure and deformation as the probe presses gently against the breast. This data is then transformed into quantitative stiffness profiles, revealing how firm or soft different areas are an important clue since tumors tend to be stiffer than healthy tissue. What makes this system truly innovative is its use of a hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks. The CNN analyzes the spatial patterns of stiffness, while the BiLSTM captures how tissue response changes over time during the probe's indentation. Together, they enhance the system's ability to detect subtle, complex tumor characteristics that might be missed by other methods. In addition to identifying tumors, the system creates a detailed heat map showing the exact location and size of stiff areas within the breast. This visual tool gives clinicians' deeper insight beyond a simple yes-or-no diagnosis, helping guide further examination or treatment planning. Extensive testing with breast tissue models containing tumor-like inclusions has shown that this smart palpation framework performs with high accuracy, consistency, and robustness even when used in realistic, freehand clinical scenarios. By integrating soft robotics, sensitive sensors, and AI-driven analysis, this approach transforms traditional breast examination into a smart, non-invasive, and data-driven process. Ultimately, this advanced system holds great promise for improving early breast cancer detection, offering patients a more comfortable experience and clinicians more reliable information to make timely, life-saving decisions.

2.1 Soft Robotic Probe

The Soft Robotic Probe Module plays a vital role in a cutting-edge tactile palpation system designed to feel like a human touch. Crafted from soft, biomimetic materials, this innovative probe gently adapts to the natural curves of breast tissue. It performs precise micro-indentations to detect subtle differences in tissue stiffness, a crucial factor in identifying tumors. What makes this module stand out is its flexibility not just in movement but in comfort as well. It applies gentle, evenly spread pressure, ensuring the patient feels at ease throughout the examination. Whether used by hand or through automated scanning, the probe delivers consistent and repeatable results, making the process both reliable and adaptable. Inside the probe, advanced Fiber Bragg Grating sensors quietly measure strain and deformation without compromising its softness. This technology allows for accurate, depth-specific readings of tissue stiffness, greatly enhancing the ability to spot potential tumors early and with confidence. In essence, the Soft Robotic Probe Module combines the sensitivity of human touch with the precision of modern technology, offering a promising tool for safer, more comfortable, and more effective breast examinations.

2.2 Multi-array FBG Sensor Network

In the world of medical technology, a breakthrough has emerged with the Multi-Array Fiber Bragg Grating (FBG) Sensor Network, a vital part of a smart tactile palpation system. This advanced network is embedded within a soft robotic probe, enabling it to gently press on tissues and measure their mechanical responses with remarkable precision. As the probe performs tiny indentations, multiple FBG sensors scattered throughout detect subtle changes in strain, providing detailed insight into how the tissue reacts. What makes these sensors truly impressive is their sensitivity they can pick up even the faintest variations in tissue stiffness, which is essential for spotting early-stage tumors. They work by converting physical deformation into shifts in light wavelengths, allowing for highly accurate and reliable measurements. Thanks to their arrangement in a multi-array setup, the system can map out tissue stiffness across different locations, helping doctors locate abnormalities and understand their size and shape. Moreover, these FBG sensors are immune to electromagnetic interference, ensuring consistent performance in busy clinical settings. The system supports real-time data collection during both manual and automated scans, capturing the dynamic behavior of tissues as they respond to pressure. The rich data collected from these sensors is then fed into a sophisticated CNN–BiLSTM model, which learns to recognize complex spatial and temporal patterns. Ultimately, this technology transforms the physical interaction between the probe and tissue into precise digital information, laying a strong foundation for reliable and early tumor detection. It's a promising step forward in making cancer diagnosis more accurate and less invasive, bringing hope to patients and healthcare providers alike.

2.3 Signal Acquisition & Preprocessing

In the world of advanced sensing technology, the Signal Acquisition and Preprocessing module plays a crucial role in transforming raw data from Fiber Bragg Grating (FBG) sensors into reliable information for analysis. These sensors detect tiny shifts in light wavelengths caused by tissue deformation, which are then captured by an optical interrogator and converted into digital strain values. To ensure the data is clean and accurate, the module applies noise filtering techniques like low-pass and Savitzky–Golay filters, removing unwanted distortions. It also corrects for baseline drift to eliminate environmental effects that could skew the results. Beyond cleaning the data, the module synchronizes and normalizes signals from multiple sensor channels, creating a consistent dataset ready for precise spatial and temporal analysis. Handling real-world challenges, the module deals with missing or corrupted data through careful interpolation and validation, ensuring no gaps undermine the study. Finally, the processed data is organized into structured formats, perfectly prepared for further steps such as stiffness calculation and powering deep learning algorithms for tumor detection. This seamless process turns complex raw signals into meaningful insights, supporting critical medical analysis with clarity and precision.

2.3 Stiffness Profile Computation

Imagine a groundbreaking tool designed to reveal the hidden stiffness within tissues, a key indicator in spotting tumors. This is the essence of the Stiffness Profile Computation module. It starts by taking detailed strain data from special sensors and transforms that raw information into precise measurements of how stiff the tissue really is. By carefully examining how tissue deforms under tiny, controlled pressure, the system can distinguish between normal and abnormal areas, since tumors tend to be much firmer than healthy tissue. The module doesn't just stop at surface-level analysis. It creates detailed maps showing stiffness across different locations and depths, allowing for a more thorough understanding of tissue characteristics. It also tracks how the tissue's stiffness changes over time during dynamic palpation, adding another layer of insight into how the tissue behaves in real conditions. What makes this system especially powerful is its ability to highlight areas of high stiffness as potential tumor sites, and it does so with flexible analysis options whether focusing on a single point or multiple points for greater accuracy. The data it produces is perfectly prepared for advanced machine learning models like CNN–BiLSTM, enabling automated, intelligent interpretation. Clinicians can then visualize this information in easy-to-understand 2D or 3D maps, helping them clearly see the size, shape, and exact location of any abnormalities, which supports better-informed decisions and patient care.

2.4 Deep Learning Tumor Detection Module (CNN-BiLSTM)

In the quest for more accurate tumor detection, a new Deep Learning Tumor Detection Module has been developed, harnessing the power of advanced artificial intelligence. This system analyzes processed stiffness data, which reveals subtle differences in tissue consistency, to spot tumors with impressive precision.

At the heart of this technology lies a hybrid architecture combining Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks. The CNN component excels at examining spatial features within stiffness maps, identifying patterns and localized abnormalities. Meanwhile, the BiLSTM part focuses on temporal patterns derived from dynamic palpation data, capturing how tissue behavior changes over time. Together, they create a powerful synergy that enhances the accuracy and reliability of tumor detection. The model doesn't just detect abnormalities; it also classifies tissue as normal or abnormal and provides confidence scores for each prediction, helping clinicians gauge the certainty of the results. To ensure robustness and adaptability, the system uses advanced techniques such as dropout, batch normalization, and data augmentation during training. Leveraging data from tissue phantoms, the module learns to recognize patterns of abnormal stiffness effectively, making it a precise and intelligent tool for identifying tumors. This innovative approach promises to improve diagnostic capabilities, offering a smart, data-driven solution that supports early and accurate tumor detection, ultimately benefiting patient care and treatment outcomes.

2.5 Stiffness Heatmap Reconstruction

In the realm of medical imaging and diagnostics, the Stiffness Heatmap Reconstruction module plays a pivotal role in transforming raw data into meaningful insights. It takes processed sensor readings and deep learning predictions and translates them into detailed spatial maps that reveal variations in tissue stiffness. By aligning these predictions with the exact physical location of the probe, the module creates vivid color-coded heatmaps in both 2D and 3D formats. These heatmaps use different colors to highlight areas of varying stiffness, making it easier to spot regions that might indicate tumors. Beyond just visualization, the module estimates the size and shape of potential tumors by analyzing the stiffness patterns it detects. It also allows these heatmaps to be overlaid on anatomical models, enhancing the clinician's understanding of the tissue landscape in a real-world context. One of its standout features is the ability to update these visualizations in real time during a scan, giving medical professionals immediate feedback. Furthermore, the module stores all quantitative data for future reference, aiding in thorough analysis and improved treatment planning. By converting complex data into clear, actionable images and insights, this technology significantly advances the accuracy of diagnoses and supports more effective clinical decisions.

2.6 Visualization & Localization Output

In modern clinical practice, having clear and actionable imaging results is crucial for effective diagnosis. The Visualization and Localization Output module steps in to meet this need by presenting stiffness heatmaps and tumor detection outcomes in a way that is both intuitive and clinically valuable. It shows color-coded maps that highlight tumor location, size, and confidence levels, enabling clinicians to quickly spot abnormal areas. What make this module especially useful are its interactive features. Clinicians can zoom in and explore the tissue characteristics in detail, gaining a deeper understanding of the patient's condition. This hands-on approach supports more accurate assessments during examinations. Moreover, the module works in real time, updating results as the examination progresses. It integrates seamlessly with existing clinical systems, making it practical for everyday use. By providing consistent, data-driven insights, it enhances objectivity and supports thorough documentation. This improves monitoring and decision-making, ultimately boosting the reliability of diagnoses and patient care.

RESULT & DISCUSSION

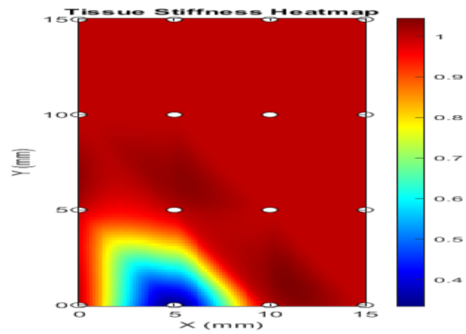

Fig.2. Tissue Stiffness Heatmap

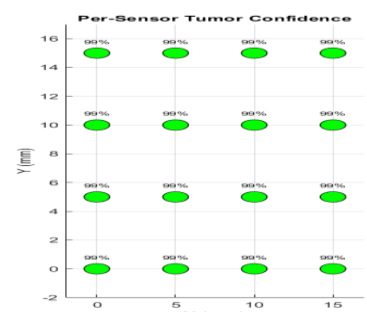

Fig 3: Per-Sensor Tumor Confidence

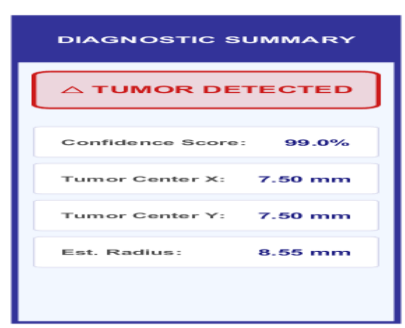

Fig.4. Diagnostic Summary Panel

A new smart tactile palpation system has been tested using synthetic datasets designed to mimic real tissue behavior. This system combines advanced fiber optic sensing with deep learning to detect and pinpoint tumor areas based on tissue stiffness. The system generates a detailed heatmap showing the stiffness across the tested region, as shown in Fig. 2. Warmer colors like red and yellow highlight areas that are stiffer, which could indicate tumors, while cooler colors like blue and green represent softer, normal tissue. Thanks to data from multiple sensors, the heatmap is smooth and highly detailed, making it easy to identify abnormal regions and their boundaries. Each sensor independently analyzes the tissue stiffness and provides a confidence score for tumor presence, as illustrated in Fig. 3. These confidence scores consistently remain around 90% or higher across different sensors. This multi-sensor agreement improves system reliability by reducing false positives and ensuring that detection is not dependent on a single sensor. The system then summarizes its findings with clinically relevant details, as shown in Fig.4, including tumor detection status, confidence score (around 99%), and estimated tumor location and size. This is achieved using a hybrid deep learning model that analyzes both spatial and temporal features for accurate diagnosis.

Overall, this approach represents a significant improvement over traditional palpation methods. By integrating fiber optic sensing, stiffness mapping, and AI, it provides a non-invasive, consistent, and data-driven solution for breast tumor detection, enabling accurate localization and improved diagnostic confidence.

CONCLUSION

Breast tumor detection is taking a leap forward with a new AI-powered smart tactile palpation system. This innovative approach blends soft robotics, Fiber Bragg Grating (FBG) sensors, and advanced deep learning to turn the traditional, subjective palpation process into a precise, data-driven diagnostic tool. At the heart of the system is a soft robotic probe embedded with FBG sensors that measure tissue stiffness in a noninvasive and highly detailed way. This design not only ensures patient comfort but also captures accurate data. The collected signals are then analyzed by a hybrid deep learning model combining CNN and BiLSTM techniques, which excels at interpreting both spatial and temporal patterns in the palpation data. This significantly boosts the system's ability to detect tumors accurately. To make the findings clear and actionable, the system generates a stiffness heatmap that visually locates tumors and estimates their size. Testing on breast tissue phantoms confirmed the system's reliability, repeatability, and user-friendly performance, whether used in controlled settings or freehand. Overall, this breakthrough represents a meaningful advance in breast cancer screening. By providing a consistent, objective, and clinically supportive method for early tumor detection, it promises to improve patient outcomes and support healthcare professionals with better diagnostic tools.

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