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Machine Learning-Based Early Breast Cancer Detection Through Temperature and Color Skin with Non-Invasive Smart Device

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ABSTRACT

Breast cancer remains a significant global health issue, affecting millions of women and often leading to late-stage diagnoses. Traditional diagnostic methods, such as mammograms, ultrasounds, and biopsies, are effective but can be costly, invasive, and not widely accessible, causing delays in detection and treatment. This research highlights the potential of using machine learning models with physiological data for early breast cancer detection. By capturing subtle physiological variations from a smart bra, the device allows real-time, non-invasive monitoring, offering a preventive solution that reduces the need for frequent clinical visits. The data were collected from a modified mannequin designed to simulate conditions related to breast cancer. To classify cancerous conditions based on temperature and color data, three machine learning models were evaluated. The Random Forest (RF) model proved to be the most effective, achieving 89% accuracy, 86.11% precision, 88.57% recall, and an F1-score of 87.33%, demonstrating strong performance in identifying complex patterns. The Support Vector Machine (SVM) achieved an accuracy of 81.25%, precision of 85.7%, recall of 80%, and an F1-score of 82.64%. The Multilayer Perceptron (MLP) exhibited an accuracy of 72%, precision of 69.69%, recall of 65.71%, and an F1-score of 67.52%, suggesting potential but requiring further optimization. These models serve as valuable tools to assist medical professionals in early screening efforts. Future research should aim to improve the models' generalizability by expanding the dataset, utilizing data augmentation, applying transfer learning, and incorporating additional variables. Clinical validation and human trials are essential next steps to evaluate the system's effectiveness.

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1. INTRODUCTION

Breast cancer remains a global health issue. The World Health Organization (WHO) predicting this trend will continue [1], [2], [3]. Breast cancer is the most common cancer in women, with 2.3 million new cases and 685.000 deaths reported in 2020 [4], [5]. This burden is not distributed equally, as the incidence and mortality rates vary significantly across regions. For instance, developed countries typically report higher incidence rates due to more effective screening programs, while developing countries face higher mortality rates because of late detection and limited access to treatment [6]. Prediction indicates that by 2040, the annual incidence of new cases is expected to rise by over 40% from 2018, surpassing 3 million cases each year [7]. Diagnosing breast cancer is a critical step in the treatment process.

Common diagnostic techniques include physical exams, mammograms, ultrasounds, and biopsies [8], [9], [10]. This method has high accuracy to detecting breast cancer but still has limitations because its implementation is complicated and expensive [11], [12]. Mammography is the primary method for breast cancer screening; however, it has limitations, including high rates of false positives and false negatives, radiation risks, and the discomfort associated with breast compression [13]. Ultrasonography, while more affordable and non-invasive, has low resolution and struggles to differentiate between benign and malignant tumors, making it primarily a supplementary technique to mammography in contrast, MRI offers high sensitivity for detecting tumors, even in dense breast tissue, and avoids radiation exposure. However, its high cost limits its feasibility for large-scale screening programs [15]. In developed countries, early detection rates have reached 60-80% [16], greatly improving outcomes. However, in developing countries, the rate of early breast cancer detection is significantly lower due to limited access to cost-effective screening technologies, leading to delayed diagnoses and survival rates of only 50-60% [17], [18]. This disparity highlights the pressing need for more affordable and efficient diagnostic tools to improve early detection to reduce breast cancer deaths globally.

The Breast Self-Examination (BSE) method focuses on identifying the early signs of breast cancer, which typically manifest as physical changes in the breast [19]. Recent studies highlight that early indicators of breast cancer often include physical changes such as lumps, alterations in skin texture, changes in skin temperature, and breast skin color [20].cost One of the main drawbacks is that BSE relies heavily on the individual's ability to consistently recognize subtle changes in the breast, which can lead to either false positives or delayed detection of actual cancer signs. American Cancer Society (ACS) have indicated that BSE is no longer recommended as a primary screening method for breast cancer. Research has shown that many women may not perform BSE regularly or correctly and BSE may lead to a high rate of false positives [21]. Alternative methods, such as clinical breast examinations (CBE) and imaging-based approaches, offer improved sensitivity and specificity but are resource-intensive, limiting their feasibility in low-resource settings [22].

These numbers show that breast cancer is a major problem in public health, and that finding and treating the disease early is essential to reducing the number of new cases. In light of these concerns, there has been advancement in the use of state-of-the-art technologies like ML and DL to the breast cancer screening process. [23], [24]. Recent improvements in breast cancer detection have largely focused on deep learning and imaging technologies. Several studies demonstrate progress in using techniques like mammography, ultrasound, and Magnetic Resonance Imaging (MRI) for cancer detection. L. Wang [25] utilized deep learning models to improve diagnostic precision, particularly in dense breast tissue, which poses challenges for traditional mammography. Additionally, Carriero, Groenhoff, Vologina, Basile, & Albera [26] explored the application of CNNs in MRI-based breast cancer detection, achieving higher diagnostic accuracy by combining multiple imaging modalities. Research indicates that ultrasound technology can be effective for breast cancer detection, especially in women with dense breast tissue. However, its limitations include challenges in identifying small or subtle cancerous changes, such as microcalcifications, which increase the risk of false positives [27]. Despite these advances, these methods remain reliant on expensive equipment and are limited to detecting physical abnormalities like lumps or microcalcifications, primarily after the cancer has developed [28]. These approaches also face limitations in terms of accessibility, especially in low-resource settings. The high costs and complexity of implementing MRI, mammograms, and other imaging techniques limit their widespread use.

In this research, the primary focus shifts to the machine learning model applies for breast cancer detection using physiological data. By utilizing the data gathered from temperature and color variations in breast tissue. Changes in breast tissue temperature and color have been identified as potential indicators of breast cancer, linked to physiological alterations in affected tissues. Research suggests that local temperature increases may result from hyperemia (increased blood flow) and heightened metabolic activity in cancerous cells [29]. Studies employing infrared thermography have observed that breast cancer is often associated with asymmetrical temperature distribution patterns between breasts, signaling potential abnormalities [30]. Furthermore, skin color changes, such as redness or darkening, may be associated with localized inflammation or tumor growth affecting the skin [31]. These findings underscore the potential of analyzing physiological data as a non-invasive method to improve early breast cancer detection. The machine learning models can detect subtle patterns that might not be immediately visible to the human eye [32]. This physiological approach addresses a critical gap in current detection methods by focusing on early biological changes that precede tumor formation, offering the potential for earlier detection. Moreover, the evaluation of different machine learning algorithms provides a comprehensive comparison of their strengths and limitations, ensuring that the best model is selected for this particular application. This study explores three distinct algorithms: “Random Forest (RF), Support Vector Machine (SVM), and Multi-layer Perceptron (MLP). These methods were chosen to analyze

temperature and color data from each side of the bra, providing insights into their effectiveness in identifying early-stage breast cancer based on subtle physiological changes.

The research makes a threefold contribution, focusing on the development of a machine learning-based approach for early breast cancer detection using physiological data. First, it introduces an innovative and cost-effective screening method that leverages temperature and color variations, addressing the limitations of traditional imaging techniques and self-examination methods. Second, it systematically evaluates the performance of various machine learning algorithms, identifying the models best suited for detecting early physiological changes associated with breast cancer. Lastly, it proposes a scalable and adaptable solution tailored for low-resource settings, representing a significant step toward achieving global equity in early breast cancer detection and care.

2. METHODS

This study focuses on developing a machine learning-based system for the early detection of breast cancer. The research aims to simulate real-world conditions for breast cancer diagnostics by leveraging clinically relevant data and systematically implementing machine learning models. The methodology used in this research is illustrated in Fig. 1.

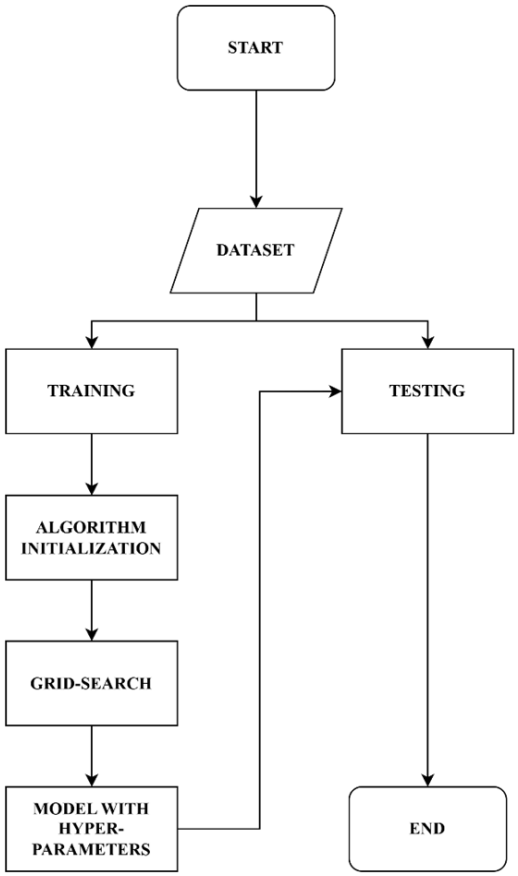

Fig. 1. Research Flow

The flowchart in Fig. 1 illustrates the workflow for developing and evaluating the machine learning model for breast cancer detection, starting from data preparation to the final optimized model. The dataset, consisting of 398 samples, is shown in Fig. 2. The data is split into 80% for training and 20% for testing, ensuring that the model is trained on the majority of the data while retaining a separate subset for unbiased evaluation. This study used three different machine learning algorithms to the problem of breast cancer case classification: Random Forest (RF), Support Vector Machine (SVM), and Multilayer Perceptron (MLP). Grid search is used as a hyperparameter tuning method to determine the optimal parameter configurations for each algorithm. Once the hyperparameter tuning is complete, the models with the best parameter settings are selected. These

optimized models are then evaluated on the testing dataset to measure their performance in terms of accuracy, precision, recall, and F1 score.

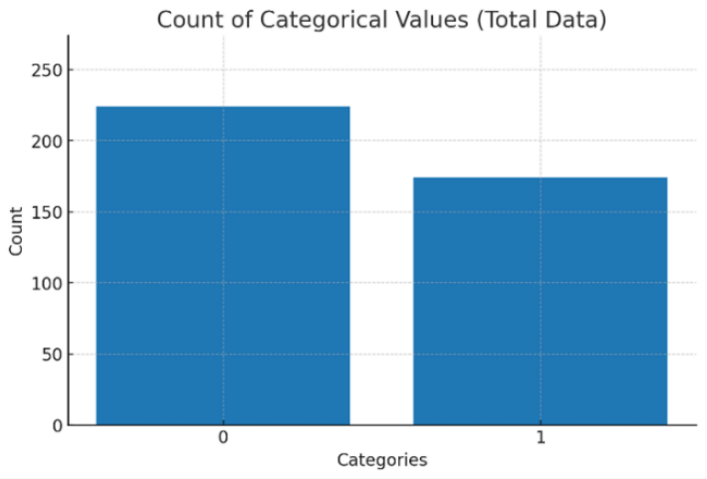

Fig. 2. Dataset (0 : Healthy, 1 : Breast Cancer)

2.1. Data Collection

Data collection was conducted in collaboration with Kucala Medical Center (KMC), ensuring the clinical relevance and validity of the dataset A modified mannequin was used to simulate conditions associated with breast cancer. The modifications included simulating skin temperature and color changes that correspond to the characteristics of breast cancer, based on input from KMC experts and relevant literature. A small, movable heating element was embedded within the mannequin to simulate tumor regions, creating temperature variations between 1°C and 3°C above the surrounding skin tissue [33], [34]. Additionally, color changes, such as redness or darkening, were simulated to mimic visual symptoms of breast cancer [35]. Data was collected from both sides of the bra (left and right), and six variables were recorded for each side has three for skin temperature and three for skin color. This detailed data structure provided a comprehensive dataset for further analysis, as illustrated in Fig. 3.

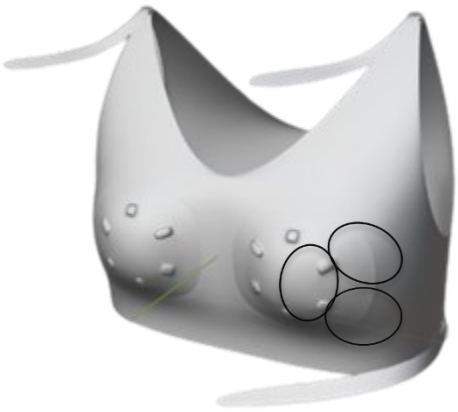

Fig. 3. Machine placement on a bra

2.2. Random Forest (RF)

RF algorithm combines concepts from decision trees and the ensemble method, specifically bagging (Bootstrap Aggregation). The algorithm combines the outputs of individual trees by majority voting (classification) or averaging (regression) [36]. The formula for a random forest classification can be expressed as:

$$f(x) = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \quad (1)$$

In this case, *T* is the total number of trees, and $h_t(x)$ is the forecast from the *t*-th tree. As a whole, deep decision trees with low bias and high variation can be averaged to lower variance. The Gini impurity or entropy is used in each tree for node splitting, based on a formula like:

$$G(p) = 1 - \sum_{k=1}^{K} p_k^2 \quad (2)$$

The RF algorithm is utilized for its ability to manage complex variable interactions and its robustness against overfitting by creating multiple decision trees and averaging their outcomes [37], [38]. This feature makes RF especially suitable for helps handle complex variable interactions, which is useful when analysing thermal and colour data from multiple regions.

2.3. Support Vector Machine (SVM)

As a classification technique, support vector machine (SVM) searches for the hyperplane that divides the data into distinct groups [28]. A binary classification problem seeks the decision border that divides the classes most clearly. One way to represent the decision function is as:

$$f(x) = w^T x + b = 0 \quad (3)$$

where w is the wight vector, x is the input data vector, b is the bias term. The objective of SVM is to maximize the margin, can be defined as $\frac{2}{\|w\|}$. SVM ties to solve the two classes in this research is as follow:

$$y_i = (w^T x_i + b) \geq 1 \quad (4)$$

where y_i is the class label (+1, -1). SVM is chosen for its efficiency in handling datasets with potentially non-linear relationships [39]. SVM uses a kernel function to create decision boundaries that can separate cancerous and non-cancerous cases effectively, even when the data points are not linearly separable [40], [41].

2.4. Multilayer Perceptron (MLP)

The Multilayer Perceptron is implemented to take advantage of its deep learning architecture. MLP's multi-layer structure helps to model intricate relationships within the dataset. MLP uses backpropagation to adjust weights during training [42]. For each neuron in the hidden layer, the output is:

$$z = f(\sum_{i=1}^{n} w_i x_i + b) \quad (5)$$

This is where the activation function *(f)*, bias term *(b)*, weight (w_i) for each input (temperature and color), and input (x_i) are defined. To minimize the loss function in MLP, gradient descent is used. The backpropogation algorithm updates the weights using:

$$w_i := w_i - \eta \frac{\partial L}{\partial w_i} \quad (6)$$

MLP can learn complex patterns and non-linear associations between the input features and breast cancer outcomes [43].

2.5. Evaluation Performance

The confusion metrix are used to quantify the performance of machine learning models. The confusion matrix is utilized to analyze the relationship between the actual classification outcomes and the predictions generated by the algorithms. The confusion matrix is shown in Table 1.

Table 1. Confusion Matrix

PREDICTION	ACTUAL	
	Positive	**Negative**
Positive	TP	FP
Negative	FN	TN

Based on Table 1, The confusion matrix comprises four main components that evaluate the performance of classification model. True Positive (TP) is represent where the model correctly predicts the positive class. True Negatives (TN) refer to instances where the model accurately predicts the negative class. False Positive (FP), also known as Type I errors is an incorrect positive prediction when the true classis negative, and False Negative (FN) or Type II error is an incorrect negative prediction when the true class is positive. These

components form the foundation for calculating key metrics such as accuracy, precision, recall, specificity, and the F1-score, which together provide a comprehensive assessment of a model's strengths and limitations in classification [44].

1) Accuracy

Accuracy measures the overall correctness of the model by calculating the proportion of correctly predicted instances (both positive and negative) out of the total instances [45]. The formula for accuracy can be represented of the equation:

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \quad (7)$$

2) Precision (Positive Predictive Value)

Precision indicates how many of the predicted positive cases are actually correct. It is critical in scenarios where false positives carry significant costs, such as when a false positive could lead to unnecessary stress or invasive procedures [46]. Precision can be calculated using the following formula:

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

3) Recall (Sensitivity or True Positive Rate)

Recall measures the proportion of actual positive cases that the model successfully identifies. It is important in applications where false negatives are costly, as failing to identify a positive case could have severe consequences [47]. The formula for recall can be expressed as follows:

$$Recall = \frac{TP}{TP + FN} \quad (9)$$

4) Specificity (True Negative Rate)

Specificity calculates the proportion of actual negatives that the model correctly predicts as negative. This metric is particularly useful in assessing the model's ability to avoid false positives. Specificity can be calculated as follows [48]:

$$Specificity = \frac{TN}{TN + FP} \quad (10)$$

5) F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives. The formula for F1-Score can be expressed as follows [49]

$$F1 - Score = \frac{2(Recall \times Precision)}{Recall + Precision} \quad (11)$$

3. RESULTS AND DISCUSSION

The main focus of this research is to develop a robust machine learning (ML) model for early breast cancer detection using physiological data, specifically temperature and color variations. This ML model is designed to process data collected through a smart bra, which serves as a non-invasive data acquisition device. To ensure accessibility and usability, the ML model is integrated into a web-based platform, enabling seamless data analysis and real-time results for users. While the smart bra and website serve as complementary components, their primary role is to support the application and effectiveness of the ML model, ultimately creating a comprehensive system for early breast cancer detection.

3.1. Machine Learning Analysis

Python performed the breast cancer detection. We built a prediction model using all the variables in the dataset to see how well machine learning methods might detect breast cancer. The model was trained with 80% of the data and evaluated using 20% using scikit-learn. The generalizability of the model was effectively evaluated using this split technique. Each model underwent extensive hyperparameter optimization to enhance its predictive accuracy and ensure that the results reflected the models' best capabilities [50].

The MLP was implemented using TensorFlow, leveraging dense layers to create a fully connected neural network architecture. For optimization, the Adam optimizer was selected due to its adaptability and efficiency in handling sparse gradients. Due to its extensive training across 80 epochs, the model was able to master the data's intricate linkages. Maximum depth was set to 90, maximum features to auto, minimum samples to split to 5, and n estimators to 80 in the RF model. These parameters were chosen to balance the depth and breadth of the decision trees while maintaining computational efficiency. The RF's ensemble approach allowed it to

aggregate the results of multiple trees, which helped mitigate overfitting and improve generalization [51]. The SVM model employed a polynomial kernel with a degree of 8, which enabled it to map the non-linear relationships in the data to a higher-dimensional space. This method is especially beneficial for managing complex boundaries between classes, as it allows the SVM to better distinguish between cancerous and non-cancerous cases. The Performance results using the confusion matrix for SVM, MLP and RF are shown in Fig. 4, Fig. 5 and Fig. 6.

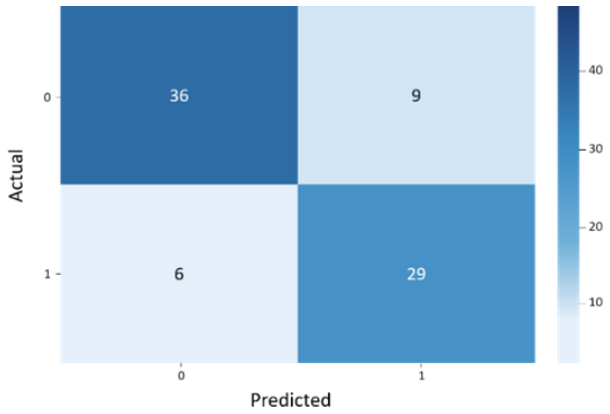

Fig. 4. Confusion matrix of SVM Model
(0: healthy; 1: breast cancer)

Fig. 4 is a representation of the confusion matrix of the SVM model, each value reflects the model's performance in distinguishing between these two classes. The True Negatives (TN), which count to 36 represent healthy areas that the model correctly identified as non-cancerous. The False Negatives (FN) witch count of 6 represents where SVM incorrectly classified cancerous areas as healthy. This type of error is especially critical because each missed cancer detection can delay both diagnosis and essential treatment, potentially impacting patient outcomes. The False Negative Rate (FNR) of this model is 20%, meaning that 20% of actual positive cases were incorrectly classified as negative. This could result from subtle physiological variations in temperature or color that the model's polynomial kernel struggles to capture in higher-dimensional space. The FP errors, where healthy tissue is classified as cancerous, suggest that the model may be overly sensitive to noise or overlapping features, leading to misclassification.

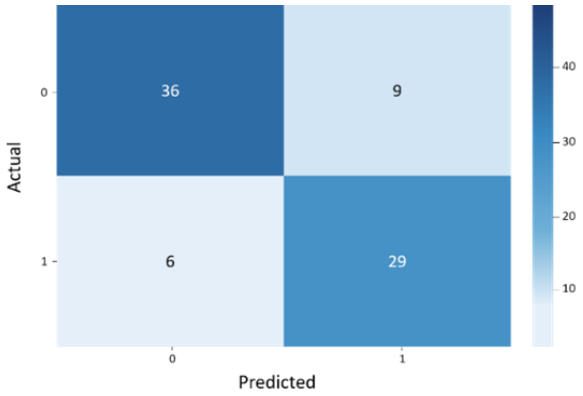

Fig. 5. Confusion matrix of MLP Model
(0: healthy; 1: breast cancer)

The confusion matrix for the MLP model in Fig. 5 highlights its performance, with 31 TN and 23 TP correctly classified. However, it recorded 12 FN and 9 FP, resulting in a high FNR (Flase Negative Rate) of 34.29%. The FN cases indicate significant limitations in detecting cancerous regions, likely due to the model's overfitting during the 80 epochs of training. This overfitting is likely due to the limited dataset size used for training, causing the model to memorize patterns specific to the training data rather than generalizing to unseen data. Neural networks, such as MLPs, typically require large and diverse datasets to learn robust representations. The small dataset may not have provided enough variation, leading the model to fit noise or

irrelevant features. Addressing this overfitting would require strategies such as increasing the dataset size through data augmentation, using cross-validation, or reducing the complexity of the MLP architecture to better align with the available data.

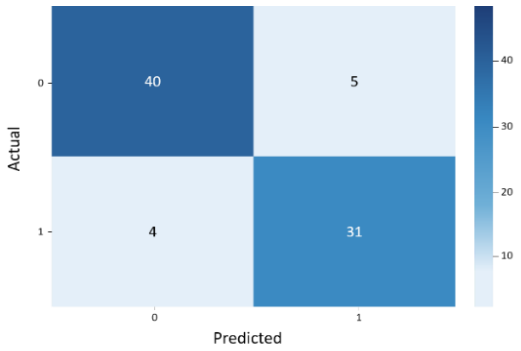

Fig. 6. Confusion matrix of RF Model
(0: healthy; 1: breast cancer)

Based on the calculations in Fig. 6, the confusion matrix for RF model achieved the best performance among the three models. It correctly identified 40 TN and 32 TP while recording only 2 FN and 4 FP, resulting in an FN rate of 11.1%. The lower FNR (False Negative Rate) suggests that the ensemble nature of RF model enabled it to capture subtle but critical features in the dataset more effectively than the other models. False negatives in medical diagnostics are particularly critical, as they may delay diagnosis and essential treatment, potentially compromising patient outcomes. Fig. 7 summarizes the results of the machine learning models.

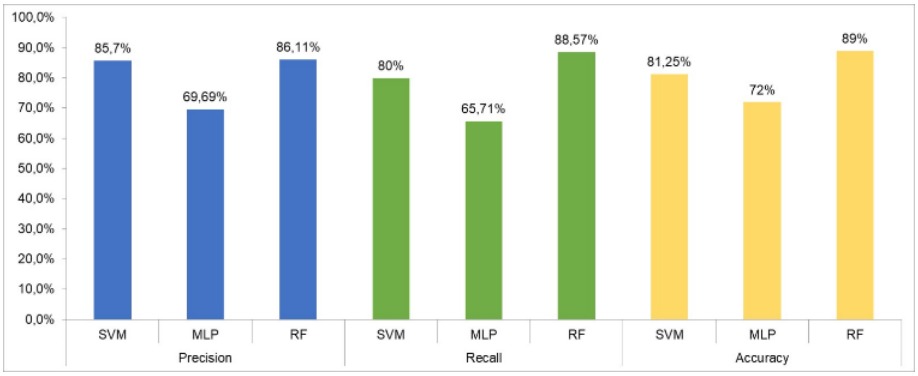

Fig. 7. The performance results of the machine learning models

Fig. 7 provides a detailed comparison of each model's effectiveness in detecting early-stage breast cancer. Random Forest (RF) consistently outperforms the other models across all metrics, achieving the highest precision (86.11%), recall (88.57%), and accuracy (89%), indicating its robustness and reliability. SVM follows closely, with solid precision (85.7%) and recall (80%), and an accuracy of 81.25%, making it a viable alternative. In contrast, MLP demonstrates the lowest performance, with precision at 69.69%, recall at 65.71%, and accuracy at 72%, suggesting it may produce more errors and is less suited for tasks requiring high prediction accuracy and sensitivity. This resulted in a, highlighting the model of MLP need for larger training datasets when applying MLPs in medical diagnostics [52]. Recall, which measures the model's ability to identify all actual positive cases, is particularly important for breast cancer detection, as missed diagnoses can delay treatment and worsen outcomes. While RF demonstrated the highest recall, the relatively lower recall of SVM (80%) and MLP (65.71%) raises concerns about their reliability for early detection.

The F1-Scores of the machine learning models are presented in Fig. 8, providing a balanced evaluation of their performance by combining precision and recall. Among the models, Random Forest (RF) achieved the highest F1-Score of 87.33%, demonstrating it's ability to accurately classify both cancerous and non-cancerous cases with minimal errors. The SVM model followed with an F1-Score of 82.64%, reflecting solid performance but slightly lower sensitivity compared to RF. The MLP model, with an F1-Score of 67.52%, exhibited the

lowest performance. This comparison highlights the robustness of the RF model and it's suitability for early breast cancer detection.

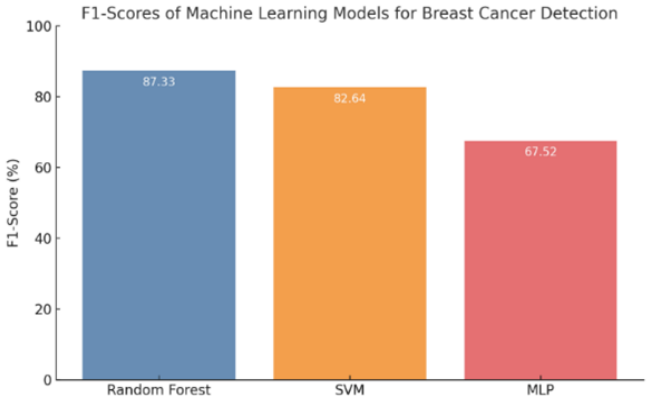

Fig. 8. F1-Score of Machine Learning

The findings of this research demonstrate the potential clinical relevance of machine learning model performance for early breast cancer detection using physiological data. These models offer a complementary tool to assist medical professionals in early screening. They are designed to enhance clinical decision making by providing additional insights into early physiological changes that may precede visible symptoms. This supplementary approach can help doctors identify potential cases more efficiently, particularly in low-resource settings where access to advanced imaging techniques may be limited, ultimately reducing diagnostic delays and improving patient outcomes.

3.2. Smart Bra

Current breast cancer detection methods, while effective, often come with significant limitations such as high costs, invasiveness, and the need for specialized equipment and clinical visits [53]. In response to these challenges, the development of a smart bra for breast cancer detection offers a more affordable, non-invasive, and accessible alternative. The smart bra (Fig. 9) includes six high-precision temperature sensors (MLX90614) and six color sensors (TCS34725), all connected through two Wemos D1 mini microcontrollers and supported by two multiplexers, a lithium battery, and a micro-USB charging module. Machine learning algorithms process the collected data, analyzing patterns in temperature and color to identify early signs of cancer with greater accuracy. This approach enhances detection capabilities, making the smart bra an effective, user-friendly tool for proactive breast health monitoring.

Fig. 9. Design of Smart Bra and Installation of the sensor on the bra cup and the controller module board on the back of the bra

Designed like a sport bra, the smart bra provides comfort and functionality for daily use. The bra is tailored to fit a range of body sizes, providing a comfortable and secure fit for the user. The placement of the sensors and electronic components is carefully planned to avoid any discomfort during wear. Each side of the bra is equipped with three temperature sensors and three-color sensors. The reliability of the smart bra relies on the accuracy of the temperature and color sensor. The MLX90614 temperature sensor, which demonstrated

a low average measurement error of 0.5°C (1%) confirms its suitability for detecting temperature variations associated with breast cancer.

When the system is activated, the sensors continuously detect temperature and color variations across the breast tissue. The microcontroller then sends the processed data to a database for additional analysis. In order to detect breast cancer early, the smart bra provides real-time monitoring of breast health, which is a practical, comfortable, and cost-effective alternative to more costly and intrusive diagnostic procedures.

3.3. Web Development

Machine learning model is integrated into a web-based platform for the diagnosis process to boost the overall functioning of the breast cancer detection system. A combination of the Tailwind-based framework and Flowbite manage the style of the project's website, which is built using HTML, CSS, JavaScript, and PHP. In order to keep track of user information and provide detection history, it incorporates a MySQL database. On the homepage, you can see the data transmitted by the "smart bra" to the database. On the history page, registered users may see their detection histories. And lastly, on the inspection results page, you can see the analysis and findings. It is possible to observe the structure and operation of these pages in fig. 7.

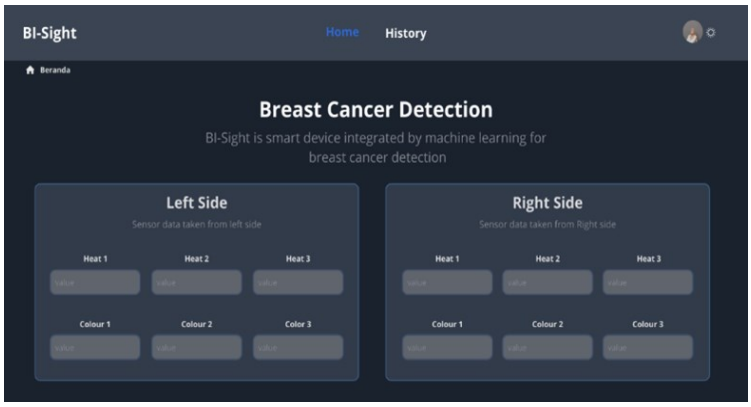

Fig. 10. Display on the website

This platform is essential for processing data collected by the smart bra where the machine learning model analyzes temperature and color variations to detect early signs of breast cancer. The website facilitates real-time data transmission, processing, and display, allowing users to monitor their health status easily. Additionally, it stores user data, detection history, and inspection results, making it a comprehensive diagnostic tool. By integrating machine learning, the system provides more accurate and timely breast cancer detection results, offering both accessibility and precision to its users.

Machine learning (ML) plays a critical role in enhancing the diagnostic capabilities of wearable technologies for early breast cancer detection. By analyzing complex physiological data, such as temperature and color variations, ML algorithms like Random Forest can detect subtle patterns indicative of early-stage tumors, which might not be apparent through direct measurement alone. In comparison, a flexible wearable thermography system that relies on bioheat microsensors to capture thermal gradients does not incorporate ML for data analysis [54]. While this system effectively maps surface temperature changes, the lack of ML integration limits its ability to process complex or borderline cases, where manual interpretation could lead to errors. This research bridges this gap by automating the detection process, improving both sensitivity and accuracy, and ensuring the system's adaptability to varying physiological conditions.

4. CONCLUSION

This research demonstrates the effectiveness of machine learning models in enhancing early breast cancer detection through non-invasive physiological monitoring. The Random Forest (RF) model achieved the highest performance, with an accuracy of 89%, a recall of 88.57%, and an F1-score of 87.33%. The Support Vector Machine (SVM) followed with an accuracy of 81.25%, while the Multilayer Perceptron (MLP) recorded the lowest accuracy at 72%, primarily due to overfitting caused by the limited dataset. The strong performance of the RF model underscores its ability to capture complex patterns in physiological data, making it a promising tool for early cancer detection. This method integrating advance machine learning models with wearable technology, provides a cost-effective, accessible, and patient-friendly which are suitable for early-stage detection. These models provide a complementary tool to assist medical professionals in early screening. The

models are designed to enhance clinical decision-making by providing additional insights into early physiological changes that may precede visible symptoms. This supplementary approach can help doctors identify potential cases more efficiently.

While the results are promising, this study has limitations. The dataset used was relatively small and imbalanced, which affected the performance of certain models, such as the MLP, and limited the overall generalizability of the findings. Additionally, the data were collected from a modified mannequin designed to simulate conditions associated with breast cancer. Future research should focus on addressing these limitations by expanding the dataset and ensuring its diversity to improve the models' generalizability. Specific efforts should include data augmentation, transfer learning, and the inclusion of additional variables to optimize the performance of models like MLP. Clinical validation and trials involving human subjects are essential next steps to evaluate the system's effectiveness.

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