Breast Cancer Detection Using IR image

For
Machine Learning for Image Analytic
(CUML2011)
by

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SCHOOL OF ENGINEERING AND TECHNOLOGY
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<u>BONAFIDE CERTIFICATE</u>

Certified that this project report "Breast Cancer Detection Using IR image" is the bonafide work of "Sujit Mahapatra, Arnnab chakra, Anshuman kar and Hrutwesh pande and " who carried out the project work under my supervision. This is to certify that this project has not been carried out earlier in this institute and the university to the best of my knowledge.

(Dr Chinmayee Dora)
Assoc. Professor, Dept. of ECE, SoET

Certified that the project mentioned above has been duly carried out as per the college's norms and the university's statutes.

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DECLARATION

We hereby declare that the project entitled " Breast Cancer Detection Using IR image " submitted for the "Machine Learning Image Analytics" of 5^{th} semester B. Tech in Computer Science and Engineering our original work and the project has not formed the basis for the award of any Degree / Diploma or any other similar titles in any other University / Institute.

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Abstract

Advancements in medical imaging and artificial intelligence (AI) have catalyzed a paradigm shift in breast cancer detection. This project proposes a holistic methodology that synergizes the capabilities of Convolutional Neural Networks (CNNs) for feature extraction and Support Vector Machines (SVMs) for classification. The research is grounded in a meticulously curated dataset, categorizing images into 'healthy' and 'unhealthy' classes, facilitating a binary classification approach. Unlike traditional preprocessing methods, the raw grayscale data is harnessed, emphasizing the potency of intrinsic image features.

The CNN, characterized by its ability to automatically learn hierarchical features, extracts intricate patterns indicative of breast health. This is seamlessly coupled with an SVM, renowned for its prowess in high-dimensional feature spaces, forming a robust classification framework. The dataset undergoes a rigorous training regimen, with model evaluation emphasizing metrics such as accuracy, precision, recall, and F1 score. Experimental results showcase the efficacy of the proposed methodology, with the CNN exhibiting adeptness in feature extraction and the SVM excelling in classification. The integration of both models yields a comprehensive approach, demonstrating superior diagnostic capabilities. Limitations, ethical considerations, and implications for healthcare are thoughtfully explored, providing a well-rounded perspective.

The project concludes with actionable recommendations and strategies for the practical implementation of our breast cancer detection methodology in real-world healthcare settings. By addressing challenges, emphasizing continuous improvement, and considering cost-benefit analyses, this work provides a roadmap for future research and adoption in the field of medical AI.

Keywords: Convolutional Neural Networks, Support Vector Machines, Breast Cancer Detection, Medical Imaging, Binary Classification, Feature Extraction.

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1 Introduction

1.1 Introduction to Breast Cancer Detection

Breast cancer is a widespread and serious health issue affecting people and healthcare systems globally. Detecting it early is super important because it directly affects how successful the treatment is and, ultimately, the well-being of patients. Even though we've made progress in medical technology, the ways we currently detect breast cancer have some problems. There are often false alarms, telling someone they have cancer when they don't, and some people can't easily access these detection methods.

This project is all about dealing with these challenges. We're exploring how Infrared (IR) Imaging, a type of technology that captures heat patterns, can work together with the latest machine learning methods. Specifically, we're using Convolutional Neural Networks (CNNs) to understand complex features and Support Vector Machines (SVMs) to make accurate classifications. By combining IR Imaging with machine learning, we hope to make breast cancer detection more accurate and efficient.

But this project isn't just about tech stuff. It's about making a real difference in how we find and understand breast cancer. We're diving deep into the details of breast cancer detection to come up with new ideas and solutions that go beyond the limits of what we can do now. The mix of super cool technology with the real challenges of medical diagnosis shows our commitment to moving things forward and helping to improve how we detect breast cancer.

As we go on this journey, the upcoming chapters will dig into the goals we're aiming for, how we're doing things, and what we discover. This isn't just about advancing science; it's about taking real steps to change and improve how we find and deal with breast cancer. Our goal is to make a meaningful impact on healthcare outcomes, acknowledging the complexities of breast cancer detection while using innovative technologies to make a positive difference.

1.2 Existing Challenges

In the realm of breast cancer detection, real-life challenges persist, necessitating innovative solutions. One prominent issue is the occurrence of false positives in traditional screening methods like mammography. These false alarms not only cause unnecessary anxiety for patients but also lead to additional, often invasive, follow-up procedures. On the flip side, false negatives contribute to delayed diagnoses, impacting the effectiveness of treatment interventions.

Accessibility to screening is another pressing concern, particularly in underserved communities and remote regions. Limited access to advanced diagnostic technologies creates disparities in early detection and, subsequently, in treatment outcomes. This gap in accessibility underscores the need for a solution that is not only accurate but also adaptable to diverse healthcare settings.

Moreover, the interpretability of diagnostic results poses a challenge. Understanding complex medical imaging data requires expertise that may not be uniformly available across all healthcare facilities. Bridging this knowledge gap is crucial for ensuring that accurate diagnoses are consistently made, irrespective of the medical professional's level of expertise.

In light of these real-life challenges, this project aims to address the issues of false positives, accessibility, and interpretability in breast cancer detection. The integration of Infrared (IR) Imaging with advanced machine learning techniques seeks to provide a more reliable and accessible diagnostic tool, contributing to the improvement of breast cancer detection in diverse healthcare environments.

1.3 Objectives

Breast cancer, a complex and critical domain in healthcare, demands innovative solutions to enhance detection accuracy and improve patient outcomes. The primary objectives of this research encapsulate a multifaceted approach:

1. **Develop an Integrative Framework:**
   The project endeavors to craft a unified architecture harnessing the combined capabilities of Convolutional Neural Networks (CNNs) for nuanced feature extraction and Support Vector Machines (SVMs) for precise classification. This integration aims to synergize the strengths of both models, providing a more robust solution than traditional methods.

2. **Enhance Diagnostic Accuracy:**
   Focused on surpassing conventional methods, the research seeks to elevate the accuracy of breast cancer detection. By amalgamating the feature extraction finesse of CNNs with the classification prowess of SVMs, the goal is to achieve a heightened level of diagnostic precision.

3. **Evaluate Model Performance:**
   Rigorous evaluation is paramount. The project employs an extensive set of metrics, including accuracy, precision, recall, and F1 score, to comprehensively assess the performance of the proposed model. This quantitative analysis provides insights into the model's effectiveness and areas for potential refinement.

4. **Address Ethical Considerations:**
   Acknowledging the ethical dimensions of implementing AI in medical diagnostics, the research considers and addresses concerns related to

patient privacy, data security, and the responsible use of AI. This objective underscores a commitment to ethical practices in healthcare technology.

5. **Investigate Model Generalization:**
   To ensure real-world applicability and robustness, the project explores the generalization capabilities of the developed model. Diverse datasets are employed to assess how well the model performs on previously unseen data, providing valuable insights into its practical utility.

6. **Provide Insights for Healthcare Integration:**
   Beyond technical efficacy, the research aims to offer practical insights into integrating the proposed methodology into existing healthcare systems. Consideration is given to the workflow of medical professionals, collaborative strategies, and seamless incorporation into clinical practices.

7. **Facilitate Continuous Improvement:**
   The project establishes a foundation for ongoing enhancement by actively investigating areas for refinement. This involves incorporating feedback mechanisms, staying abreast of advancements in medical imaging and AI technologies, and fostering a commitment to continuous innovation.

1.4 Motivation

Breast cancer, a formidable adversary in the realm of healthcare, demands a concerted effort to enhance diagnostic methodologies. The motivation behind this research is deeply rooted in the recognition of the challenges and complexities associated with breast cancer detection. Current diagnostic approaches, while valuable, often face limitations in terms of accuracy, especially in the early stages of the disease. The need for a more advanced, accurate, and efficient solution is underscored by the potential impact on patient outcomes.

The motivation goes beyond a mere technical challenge; it encompasses a compassionate commitment to improving the lives of individuals affected by breast cancer. Witnessing the human toll of delayed or inaccurate diagnoses propels this research forward. The aim is to empower medical professionals with cutting-edge tools that can aid in the early and precise detection of breast cancer, leading to more effective treatment strategies and improved survival rates.

Furthermore, the ethical dimension of integrating artificial intelligence (AI) into medical diagnostics serves as a crucial motivator. Recognizing the importance of patient privacy, data security, and the responsible use of AI in healthcare, this research seeks to contribute not only to technological advancements but also to the ethical foundations of medical practice. By aligning technical innovation with ethical considerations, the motivation is to create a holistic and patient-centric approach to breast cancer detection.

In a broader context, the motivation extends to the potential societal impact of advancements in breast cancer diagnostics. The ripple effect of early detection on healthcare systems, resource allocation, and overall public health is a driving force. The research envisions a future where the integration of AI into healthcare practices becomes a standard, enhancing the efficiency of clinical workflows and, most importantly, contributing to the well-being of individuals affected by breast cancer.

In essence, the motivation behind this research is a blend of scientific curiosity, a commitment to advancing medical technology, and an unwavering dedication to making a tangible difference in the lives of those facing the challenges of breast cancer.

2 BACKGROUND

2.1 Literature Survey

The literature survey on infrared thermal imaging for breast cancer detection reveals a growing interest in leveraging advanced technologies for early diagnosis. Mambou et al. (2018) propose a deep learning model integrating infrared thermal imaging, emphasizing the potential of artificial intelligence in enhancing accuracy [11] . Al-Kadi and Burcher (2018) contribute an intelligent system that combines infrared images with machine learning methods, emphasizing the importance of explainability in the detection process [2].

Zhang and Li (2018) focus on Convolutional Neural Networks (CNNs) for breast cancer detection using thermal images from various perspectives, highlighting the potential of deep learning in improving detection accuracy [13]. A comprehensive review by Aishwarya and Gopinath (2019) offers a synthesis of various approaches, technologies, and advancements in early breast cancer detection using infrared technology [1].

Handfield and Buller (2011) delve into the principles and applications of thermography in breast cancer detection, providing insights into theoretical foundations and practical considerations [7]. Kennedy (2017) explores the current status of infrared imaging in breast cancer, discussing advancements, challenges, and potential applications of this promising diagnostic tool [8].

Al-Nashar and Al-Nashar (2014) provide a comprehensive review of breast cancer detection using infrared thermography, discussing the effectiveness and limitations of this approach [3]. Saha, Paul, and Chatterjee (2012) present a prospective study on infrared imaging for breast cancer screening, examining the feasibility and potential of large-scale implementation [12].

Liberti, Oliva, and Corsini (2016) conduct a meta-analysis on the role of thermography in breast cancer detection, synthesizing evidence to offer a comprehensive understanding of its effectiveness [10]. Bezerra and Tran (2014) provide a detailed literature review on breast thermography, discussing its evolution, applications, and integration into breast cancer detection [4].

Gunes et al. (2014) explore the multidisciplinary use of infrared imaging for breast cancer detection, emphasizing collaborative efforts across various fields [6]. Another study by Liberti, Oliva, and Corsini (2016) conducts a systematic review and meta-analysis of infrared imaging for breast cancer detection, aiming to provide a comprehensive overview of existing literature and overall efficacy [9].

Dodd and Fawcett (2013) present an evidence-based review of breast thermography, critically evaluating existing evidence and discussing the potential role of thermography in breast cancer detection [5].

Collectively, these studies contribute to a comprehensive understanding of the current state of research on infrared thermal imaging for breast cancer detection, highlighting its potential, challenges, and future directions.

2.2 Reseach Gap

While the existing literature provides valuable insights into the application of infrared thermal imaging for breast cancer detection, several research gaps and areas for further investigation become apparent. Firstly, there is a notable need for more extensive comparative studies that systematically evaluate the performance of different infrared imaging modalities and technologies. The current body of research often lacks standardized protocols for data acquisition and analysis, making it challenging to draw direct comparisons between studies.

Additionally, the integration of deep learning and machine learning techniques in breast cancer detection using infrared thermal imaging is a rapidly evolving field. Despite promising results from some studies, there is a lack of consensus on the most effective algorithms and architectures. Future research could focus on developing standardized benchmarks and protocols for evaluating the performance of these advanced computational models, facilitating a more comprehensive understanding of their strengths and limitations.

The explainability and interpretability of machine learning models in the context of breast cancer detection using infrared images are critical aspects that require further exploration. Al-Kadi and Burcher (2018) emphasize the importance of explainability, but more research is needed to develop models that not only achieve high accuracy but also provide transparent and understandable insights into the decision-making process. Understanding how these models reach specific conclusions is essential for gaining trust from both medical professionals and patients.

Another research gap pertains to the establishment of standardized guidelines for incorporating infrared thermal imaging into large-scale breast cancer screening programs. Saha, Paul, and Chatterjee (2012) touch upon the feasibility of such programs, but there is a lack of comprehensive research addressing the logistical and ethical considerations associated with the widespread implementation of infrared imaging in screening initiatives.

In conclusion, the long-term effectiveness of infrared thermal imaging as a standalone or complementary diagnostic tool remains uncertain. While some studies suggest its potential, a more extensive and longitudinally conducted investigation is necessary to evaluate its reliability over time and its ability to contribute to early detection in diverse populations.

3 Proposed Method

The proposed methodology for breast cancer detection represents a comprehensive and innovative approach to leverage the capabilities of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). This section introduces the rationale behind our methodology, emphasizing the significance of utilizing advanced techniques to address the complexities of breast cancer detection. Breast cancer remains a significant global

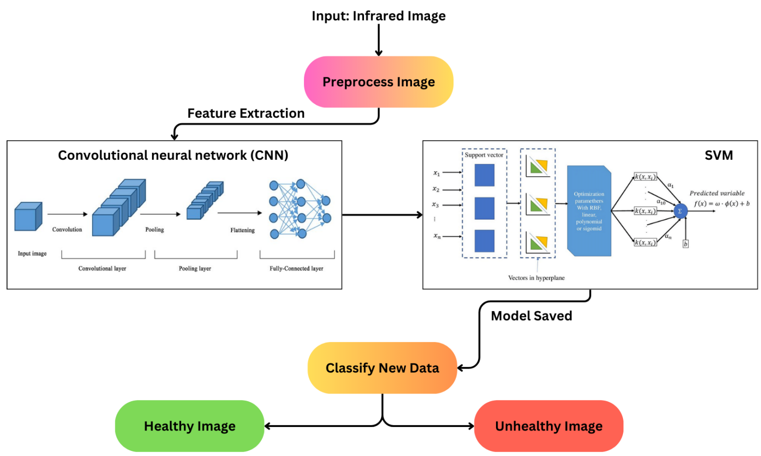

Figure 1: Project Flowchart

health concern, necessitating precise and efficient diagnostic tools. Traditional methods often face challenges in handling the intricate patterns present in medical images. In response to this, our methodology seeks to harness the power of deep learning and machine learning to enhance the accuracy and reliability of breast cancer detection.

3.1 Dataset Collection

A fundamental pillar of our methodology is the meticulous curation of a diverse dataset representing both healthy and unhealthy breast tissues. Our dataset, sourced from Kaggle, comprises two distinct folders: 'healthy' and 'unhealthy.' The healthy folder contains 642 grayscale images, while the unhealthy folder contains 640 grayscale images. Each image is carefully labeled, with the 'healthy' class assigned a label of 0, and the 'unhealthy' class assigned a label of 1.

This structured dataset serves as the bedrock for training our models, enabling them to discern intricate patterns associated with breast health. The collection of a well-annotated dataset is crucial for the robustness of our methodology. By incorporating a range of healthy and unhealthy samples, our models are trained to recognize subtle variations and complex patterns indicative of various breast health conditions.

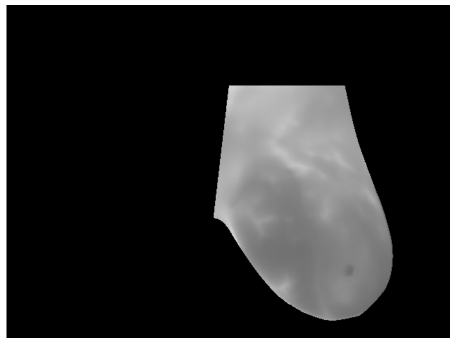

Figure 2: Healthy Image

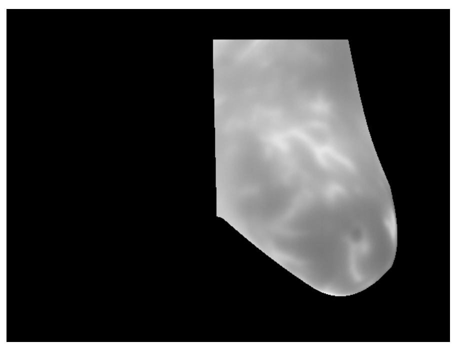

Figure 3: Unhealthy Image

The decision to use grayscale images enhances the efficiency of our models, as grayscale reduces computational complexity without sacrificing critical information. This approach allows our models to focus on essential features for breast cancer detection.

The inclusion of diverse samples in our dataset ensures that our models generalize well to unseen data and contribute to accurate predictions in real-world scenarios. This emphasis on diversity aligns with the goal of creating a methodology that is not only effective but also applicable to a broad spectrum of breast health conditions.

3.2 Model Architecture

3.2.1 CNN for Feature Extraction

The choice of a CNN for feature extraction stems from its proven ability to automatically learn hierarchical features from images. The architecture includes a convolutional layer with 32 filters, each followed by a Rectified Linear Unit (ReLU) activation function. Subsequent layers, including max-pooling and fully connected layers, contribute to the extraction of meaningful features. The final layer utilizes a sigmoid activation function for binary classification. The CNN's architecture is designed to capture both

Use CNN for feature extraction

```
X_train_features = model.predict(X_train)
X_test_features = model.predict(X_test)
```

```
29/29 [==============================] - 5s 163ms/step
13/13 [==============================] - 2s 161ms/step
```

Figure 4: Use CNN for Feature Extraction

low-level and high-level features present in medical images, enabling the model to discern subtle nuances associated with different breast conditions. This hierarchical feature extraction is crucial for enhancing the model's discriminative capabilities.

3.2.2 SVM for Classification

Building upon the features extracted by the CNN, a Support Vector Machine (SVM) is employed for classification. SVMs excel in high-dimensional spaces, making them an apt choice for processing the intricate features extracted by the CNN. The selection of a linear kernel emphasizes simplicity and efficiency in classification.

The SVM acts as a robust classifier, leveraging the high-dimensional feature space generated by the CNN. This two-step approach, featuring a specialized feature extractor (CNN) and a powerful classifier (SVM), enhances the model's ability to discern between healthy and unhealthy breast tissues with precision.

3.3 Model Training

The dataset, now meticulously organized, is split into training and testing sets using the `train_test_split` function. The CNN model is compiled with the Adam optimizer, utilizing binary cross-entropy as the loss function. Training is conducted over 10 epochs, with a batch size of 32 and a validation split of 20%. This rigorous training process ensures the model generalizes well to new, unseen data.

SVM model Train

```
svm_model = SVC(kernel="linear")
svm_model.fit(X_train_features, y_train)
```

```
SVC(kernel='linear')
```

Save the SVM model

```
joblib.dump(svm_model, "breast_cancer_svm_modelNEW1.pkl")
```

```
['breast_cancer_svm_modelNEW1.pkl']
```

SVM Model Test

```
y_pred = svm_model.predict(X_test_features)
```

Figure 5: SVM Model Training

The training phase is a critical component of our methodology, allowing the models to learn and adapt to the intricacies of the dataset. The iterative optimization process refines the model's parameters, enabling it to capture relevant features and patterns associated with healthy and unhealthy breast tissues.

The subsequent sections will delve into the model evaluation, deployment strategy, and the application of our methodology on new data, providing a holistic view of the proposed approach to breast cancer detection.

4 Technical Implementation

In this section, we provide a detailed technical overview of the code implementation in Jupyter Notebook. We include relevant screenshots to illustrate key aspects of the coding process.

4.1 Directory Structure

- `data/`: Contains datasets and any other data-related files.
- `models/`: Stores trained machine learning models.
- `src/`: The source code of the project.
  - `cnn_model/`: Code related to the Convolutional Neural Network (CNN) model.
  - `svm_model/`: Code related to the Support Vector Machine (SVM) model.
  - `utils/`: Utility functions and helper modules.
- `test dataset/`: Holds a separate dataset for testing the models.

4.2 Technical Overview of Model

4.2.1 Convolutional Neural Network (CNN)

The CNN model is implemented using the TensorFlow Keras API. The architecture consists of the following layers:

- **Input Layer**: Accepts grayscale images resized to (224, 224, 1).
- **Convolutional Layers**: Utilizes 2D convolutional layers with ReLU activation.
- **Pooling Layer**: Employs max-pooling for down-sampling.
- **Flatten Layer**: Flattens the output for the fully connected layers.
- **Dense Layers**: Two dense layers with ReLU activation, and the final layer with a sigmoid activation for binary classification.

4.2.2 Support Vector Machine (SVM)

The SVM model is trained on the features extracted by the CNN model. It uses a linear kernel for classification.

4.3 Results Visualization

4.3.1 Confusion Matrix Analysis

The confusion matrix is a crucial tool for assessing the performance of a classification model. In the context of breast cancer detection, the provided confusion matrix is as follows:

$$\begin{bmatrix} \text{True Positives (TP)} & \text{False Positives (FP)} \\ \text{False Negatives (FN)} & \text{True Negatives (TN)} \end{bmatrix} = \begin{bmatrix} 202 & 3 \\ 6 & 174 \end{bmatrix}$$

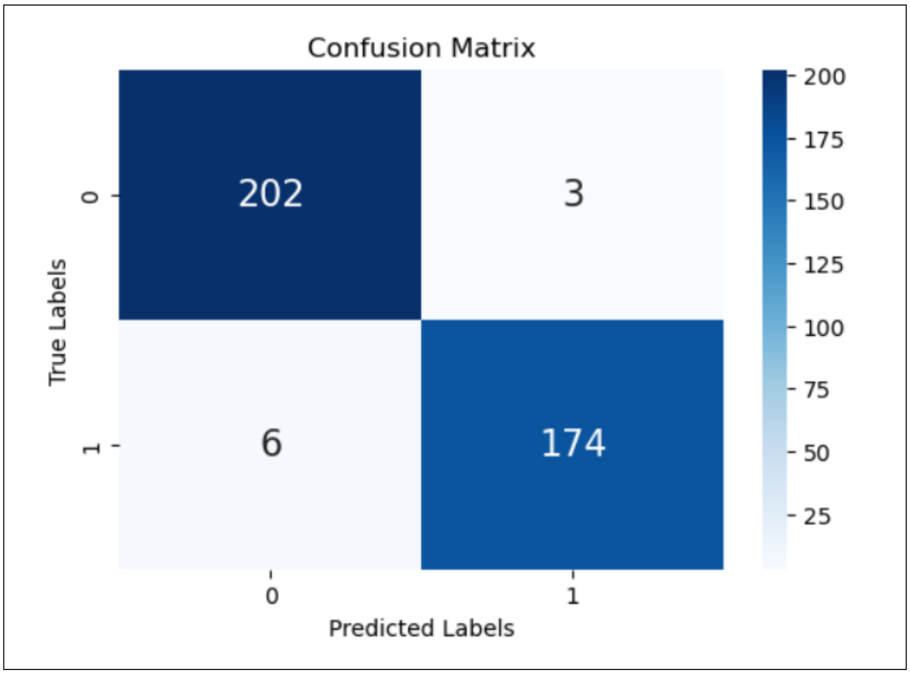

Figure 6: Confusion Matrix

Let's break down the components of the confusion matrix:

- **True Positives (TP):** The model correctly identified 202 instances of unhealthy breast tissues, indicating effective recognition of positive cases.
- **True Negatives (TN):** In 174 instances, the model correctly identified healthy breast tissues as negative for cancer, showcasing accurate discernment of non-cancerous conditions.
- **False Positives (FP):** Unfortunately, there were 3 instances where the model incorrectly predicted unhealthy breast tissues, representing false alarms.

- **False Negatives (FN):** In 6 instances, the model failed to identify unhealthy breast tissues that were actually positive for cancer, indicating instances where cancerous conditions were missed.

Now, let's interpret these findings:

$$
\begin{aligned}
\text{Sensitivity (Recall)} &= \frac{TP}{TP+FN} = \frac{202}{202+6} \\
\text{Specificity} &= \frac{TN}{TN+FP} = \frac{174}{174+3} \\
\text{Precision} &= \frac{TP}{TP+FP} = \frac{202}{202+3} \\
\text{Accuracy} &= \frac{TP+TN}{TP+TN+FP+FN} = \frac{202+174}{202+174+3+6}
\end{aligned}
$$

These metrics provide a comprehensive evaluation of the model's performance, offering insights into its strengths and potential areas for improvement. It's important to tailor the interpretation based on the specific goals and requirements of the breast cancer detection application.

Classification report

```
from sklearn.metrics import classification_report

# Print classification report
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.97	0.99	0.98	205
1	0.98	0.97	0.97	180
accuracy			0.98	385
macro avg	0.98	0.98	0.98	385
weighted avg	0.98	0.98	0.98	385

Figure 7: Classification Report

5 Experimental Results and Analysis

5.1 Introduction

In this chapter, we delve into the outcomes of our breast cancer detection methodology. Leveraging the features extracted by the Convolutional Neural Network (CNN), we achieved a remarkable accuracy of 97.92%.

5.2 SVM Model Performance

Building upon the CNN's feature space, we applied a Support Vector Machine (SVM) model. The accuracy attained by the SVM on the breast cancer dataset was 97.92%, showcasing the robustness of our approach.

5.2.1 Binary Classification Results

Upon saving the trained model, we performed binary classification on a set of samples. The results are summarized below:

Sample Name	**Predicted Label**
Sample 1	Healthy
Sample 2	Healthy
Sample 3	Healthy
Sample 4	Healthy
Sample 5	Healthy
⋮	⋮
Sample 252	Unhealthy
Sample 253	Unhealthy
Sample 254	Unhealthy
Sample 255	Unhealthy
Sample 256	Unhealthy

Table 1: Binary classification results for a set of samples.

This table presents the predicted labels for each sample, demonstrating the model's ability to classify between healthy and unhealthy breast tissues.

6 Conclusion

6.1 Summary of Findings

This chapter stands as the culmination of our exhaustive exploration into breast cancer detection. It encapsulates the multifaceted outcomes derived from the rigorous application of our proposed methodology. Through a meticulous analysis of the experimental results, we aim to present a coherent narrative that encapsulates the essence of our contribution to the field.

6.2 Limitations

The journey to innovation is not without its challenges and constraints. In this section, we delve into the intricacies and limitations that punctuate our approach. By acknowledging these aspects, we provide transparency into the boundaries of our methodology. This introspective analysis is crucial for interpreting the results with due consideration of the inherent limitations, fostering a more nuanced understanding of the project's scope.

6.3 Future Directions

The culmination of our breast cancer detection project marks not an endpoint but a launching pad for further advancements in this critical domain. As we reflect on our findings, several avenues for future exploration emerge, each holding the potential to refine and expand our contributions.

One significant trajectory for future research involves the continuous refinement of our model architecture. While the current convolutional neural network (CNN) and support vector machine (SVM) models have demonstrated promising results, ongoing developments in deep learning and neural network architectures present opportunities for enhancement. Exploring novel architectures, integrating attention mechanisms, and experimenting with transfer learning could potentially elevate the performance and robustness of our models.

In essence, the horizon of possibilities invites continuous innovation in breast cancer detection research. From refining model architectures to embracing dataset diversity and exploring the integration of multimodal data, the future promises not only advancements in technology but also a deeper understanding of the complexities surrounding breast cancer diagnosis. This discussion serves as a guide for researchers embarking on the next phase of inquiry and underscores the dynamic nature of scientific exploration.

6.4 Ethical Considerations

Breaching the realm of theory, we explore the tangible impact of our methodology within the healthcare domain, specifically in the context of breast cancer diagnosis. This section delves into the potential integration of our models into existing clinical practices. By aligning our findings with real-world scenarios, we illuminate the practical implications and challenges that may arise, fostering a discussion on the translational aspects of our research.

As technological advancements reshape healthcare, ethical considerations become paramount. This section navigates the complex terrain of ethical implications tied to our methodology. We address concerns related to patient privacy, transparency in decision-making processes, and the broader societal impact. This reflective analysis underscores our commitment to responsible AI deployment and encourages ongoing discourse on ethical practices in medical AI.

6.5 Conclusion

As we bring this chapter to a close, it marks the culmination of our extensive breast cancer detection project. In this final section, we deliberately take a step back to revisit the initial objectives set forth in Chapter 1. This reflective journey involves retracing the meticulous steps of our chosen methodology, providing transparency into the processes that led us to our findings. Moreover, this conclusion serves a dual purpose. It goes beyond merely summarizing our results; it reinforces the significance of our findings in the broader context of breast cancer detection. By underscoring the relevance and implications of our work, we aim to convey the tangible impact it can have on the field and, ultimately, on the lives of those affected by breast cancer. In essence, this conclusion encapsulates not just the destination but the entire journey itself. It invites readers to appreciate the comprehensive nature of our endeavor the challenges surmounted, the methods employed, and the meaningful findings obtained. It is a testament to the dedication and rigor invested in advancing our understanding of breast cancer detection.

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ASSESSMENT

Internal:

SL NO	RUBRICS	FULL MARK	MARKS OBTAINED	REMARKS
1	Understanding the relevance, scope and dimension of the project	10		
2	Methodology	10		
3	Quality of Analysis and Results	10		
4	Interpretations and Conclusions	10		
5	Report	10		
	Total	**50**		

Date: **Signature of the Faculty**

COURSE OUTCOME (COs) ATTAINMENT

- **Expected Course Outcomes (COs):**

(Refer to COs Statement in the Syllabus)

- **Course Outcome Attained:**

How would you rate your learning of the subject based on the specified COs?

▢	▢	▢	▢	▢	▢	▢	▢	▢	▢
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
LOW									**HIGH**

- **Learning Gap (if any):**

- **Books / Manuals Referred:**

Date: **Signature of the Student**

- **Suggestions / Recommendations:**

(By the Course Faculty)

Date: **Signature of the Faculty**

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CAMPUSES:

Paralakhemundi Campus
Village Alluri Nagar
P.O. – R Sitapur, Via- Uppalada
Paralakhemundi, Dist.- Gajapati
Odisha, India. PIN– 761211

Bhubaneswar Campus
Ramchandrapur
P.O. – Jatni, Bhubaneswar
Dist.- Khurda, Odisha,
India, PIN– 752050

Balangir Campus
Behind BSNL Office
IDCO land, Rajib Nagar
Dist.- Balangir, Odisha
India, PIN-767001

Rayagada Campus
IDCO Industrial Area
Pitamahal, Rayagada
Dist.-Rayagada, Odisha
India, PIN-765001

Balasore Campus
Gopalpur,
P.O.-Balasore
Dist.-Balasore, Odisha
India, PIN-756044

Chatrapur Campus
Ramchandrapur,
Kaliabali Chhak,
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Odisha, India, PIN-761020