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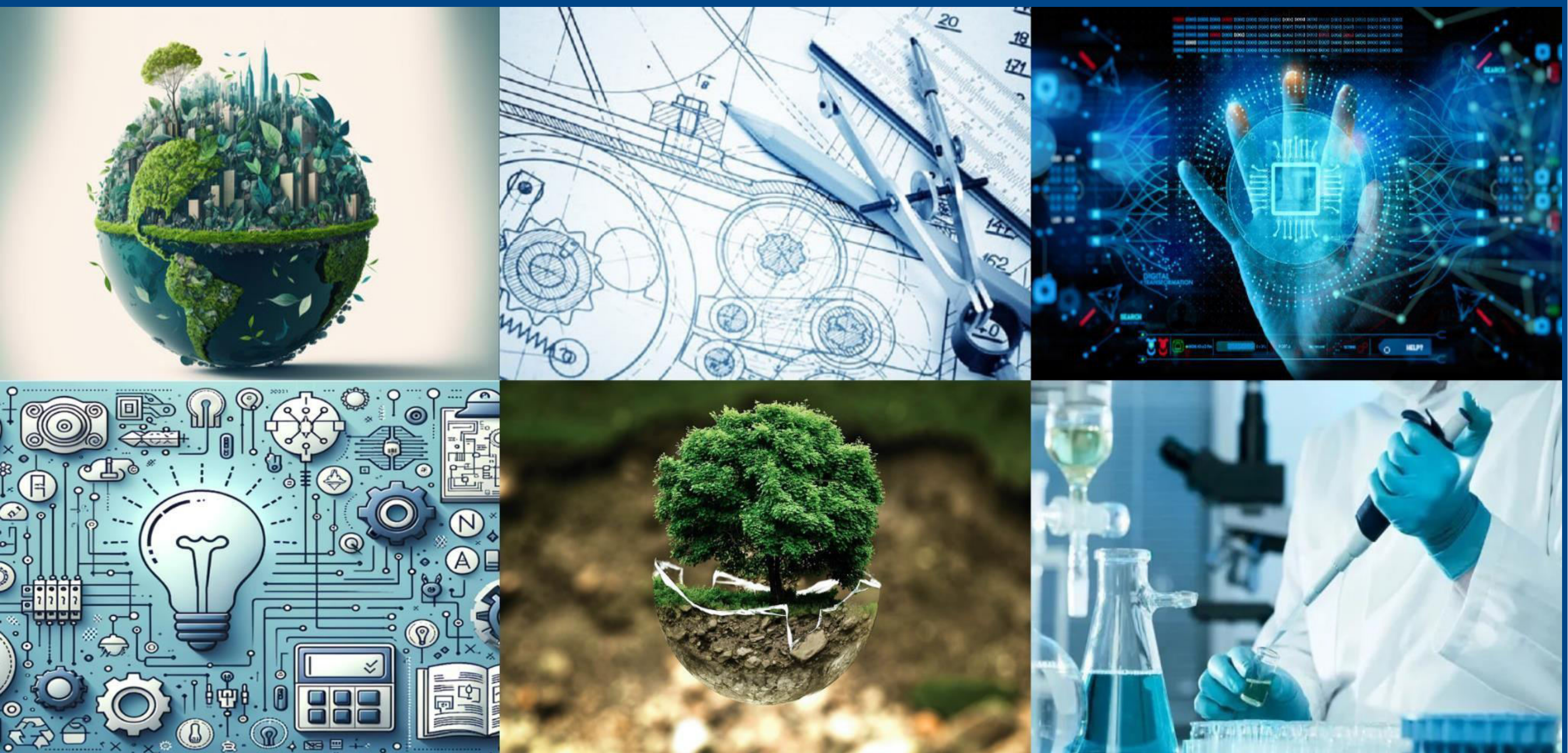

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Advancements in Hybrid Deep Learning for Breast Cancer Classification

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ABSTRACT: Early and precise diagnosis of breast cancer is paramount for enhancing patient survival rates and facilitating effective treatment strategies. This paper introduces an innovative hybrid diagnostic framework that integrates a custom-designed Convolutional Neural Network (CNN) for robust feature extraction with a Support Vector Machine (SVM) classifier for accurate final prediction. The CNN component is meticulously trained on the comprehensive CBIS-DDSM mammogram dataset, and the rich, intermediate features derived from its penultimate layer are subsequently employed to train the SVM model. This methodological separation of feature learning from classification is specifically engineered to mitigate common limitations associated with purely deep learning models, such as susceptibility to overfitting and a heavy reliance on vast, meticulously labeled datasets. The efficacy of the proposed system is rigorously evaluated using a suite of standard classification metrics, including accuracy, precision, recall, F1-score, and the Receiver Operating Characteristic-Area Under the Curve (ROC-AUC) score. Empirical results demonstrate that this CNN-SVM hybrid approach achieves a notable accuracy of approximately 91.7%, thereby surpassing the performance of several existing methodologies documented in the scientific literature. This framework represents a significant advancement in computer-aided breast cancer diagnosis, offering a promising tool to bolster clinical decision support systems

KEYWORDS: Breast Cancer Detection, Mammogram Images, Hybrid Deep Learning, Convolutional Neural Networks, Support Vector Machines, Medical Imaging.

I. INTRODUCTION

Breast cancer remains a formidable global health challenge, standing as one of the primary causes of cancer-related mortality among women, with a particularly alarming increase in incidence rates within developing nations. The World Health Organization (WHO) consistently emphasizes that early detection and timely diagnosis are critical determinants for significantly improving patient outcomes and survival prospects [1]. Historically, conventional diagnostic modalities, encompassing physical examinations, biopsies, and various radiological imaging techniques, have been characterized by their time-intensive nature, inherent susceptibility to human interpretive errors, and a considerable dependence on the subjective expertise of medical professionals.

In recent decades, the exponential growth of digitized mammogram data, coupled with transformative advancements in computational technologies, has paved the way for the emergence of artificial intelligence (AI) and deep learning methodologies as exceptionally potent tools. These technologies are increasingly instrumental in assisting radiologists to achieve more accurate and rapid detection of breast cancer [2- 4]. However, the intricate and highly variable nature of mammographic images presents a significant challenge, wherein the subtle visual distinctions between benign and malignant tissues can be profoundly nuanced and difficult to discern.

While fully supervised deep learning models, notably Convolutional Neural Networks (CNNs) [5], have exhibited remarkable capabilities in discerning these complex patterns, their effective training often necessitates exceptionally large, well-annotated datasets and substantial computational resources. Such prerequisites are not always readily available or feasible within the constraints of real-world clinical environments. Furthermore, end-to-end deep learning models frequently contend with issues such as overfitting, diminished generalizability to unseen data, and a notable lack of interpretability—factors that collectively impede their widespread clinical adoption.

The contemporary scientific literature reflects a concerted effort to address these multifaceted challenges through diverse strategies. Transfer learning approaches, leveraging pre-trained models like MobileNetV2, VGG19, and ResNet-50 [6-12], have been widely adopted to capitalize on pre-learned features for breast cancer classification. Concurrently, hybrid architectural designs have gained prominence, wherein CNNs are strategically employed for feature extraction, and traditional machine learning classifiers, such as Support Vector Machines (SVMs), are

subsequently utilized for the ultimate classification task. These hybrid methodologies often achieve an optimal balance between diagnostic accuracy and computational efficiency. Numerous studies have reported accuracies ranging from 85% to 96%, contingent upon the specific dataset and model complexity, with many models rigorously evaluated on publicly accessible datasets including CBIS-DDSM, BreakHis, and BUSI.

This research endeavors to introduce a novel custom CNN model, meticulously engineered for the specific nuances of mammogram analysis, which is then synergistically integrated with an SVM classifier to form a robust hybrid diagnostic framework. Our bespoke CNN is precisely calibrated to extract both spatial and hierarchical features from mammographic images. These extracted features are subsequently flattened and fed into an SVM for classification [16-17]. This deliberate decoupling of feature learning from the classification stage allows us to harness the formidable representational power of CNNs while simultaneously benefiting from the inherent robustness of SVMs in defining decision boundaries, a particularly advantageous characteristic in scenarios characterized by limited data availability. Moreover, this framework inherently supports interpretable evaluation through the extraction and meticulous analysis of activations from various convolutional and pooling layers.

The core innovation of this study resides in the seamless integration of a deeply customized CNN architecture with a classical machine learning classifier, specifically optimized for the intricate task of mammogram image classification. In contrast to generic pre-trained models, our CNN is trained de novo on the CBIS-DDSM dataset [18], thereby ensuring the acquisition of highly domain-specific feature representations. Furthermore, we introduce a sophisticated mechanism for visualizing intermediate feature maps and meticulously tracking training behavior through saved model history, thereby significantly enhancing transparency and interpretability. The proposed methodology not only yields superior classification accuracy but also establishes a scalable and inherently explainable framework, rendering it highly suitable for real-time clinical deployment.

II. LITERATURE REVIEW

The application of deep learning techniques in the realm of breast cancer detection has witnessed a significant surge in prominence over recent years, primarily owing to

its unparalleled capacity to automate and substantially enhance diagnostic accuracy. A diverse array of research endeavors has meticulously explored both the utility of pre- trained models and the development of custom-designed architectures for the classification of mammographic and histopathological images of breast tissue.

Jyoti Pandurang Kshirsagar et al. [1] pioneered a transfer learning approach, employing the MobileNet-V2 architecture for the classification of breast cancer images sourced from the CBIS-DDSM dataset. Their work reported an accuracy of 87% and underscored the critical importance of comprehensive evaluation metrics, including precision, recall, and F1-score. In a parallel effort, Konda Srinivasa Rao and Kalla Yogeswara Rao [2] devised a bespoke CNN architecture, specifically engineered to capture intricate tissue features, achieving a commendable classification accuracy of 93.285% utilizing data procured from Kaggle. Both studies unequivocally demonstrate the efficacy of leveraging either pre-trained or custom-built neural networks for advanced medical image analysis.

Further expanding on the application of deep learning, Mohammed Alotaibi et al. [3] ingeniously integrated the VGG19 model with sophisticated image fusion techniques, applying their methodology to ultrasound images derived from the BUSI and KAIMRC datasets. Their approach, validated through five-fold cross-validation, yielded accuracies of 87.8% and 85.2%, respectively. Concurrently, a comprehensive systematic review conducted by Maged Nasser and Umi Kalsom Yusof [4] meticulously analyzed numerous CNN-based methodologies, culminating in the definitive conclusion that Convolutional Neural Networks remain the most widely adopted and consistently accurate models for breast cancer diagnosis across a spectrum of datasets and image modalities.

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Ch. Rajendra Prasad and Soma Amulya [5] performed an exhaustive comparative analysis of various CNN architectures, including Inception-V3, VGG19, and ResNet-50, employing histopathological images for their evaluation. Their findings indicated that Inception-V3 consistently outperformed other models when synergistically paired with the Adam optimizer. In a separate investigation, Zahrah Jadah and Aisha Alfitouri [6] rigorously tested an ALEXNET-based deep learning architecture on the BreakHis dataset, demonstrating that meticulously tuned hyperparameters enabled the model to achieve an impressive 96% classification accuracy.

The concept of hybrid methodologies has also gained considerable traction. Sobia Shakeel and Gulistan Raja [7] proposed a hybrid system that initially extracts features using a custom CNN, subsequently employing an SVM for the classification task, which

resulted in an 88.7% accuracy on mammogram images. Abbas Qaisar et al. [8] adopted a distinct strategy, integrating deep learning with ensemble methods such as majority voting, and successfully achieved a 95.6% accuracy on the BreakHis dataset.

Recent advancements also include the exploration of transfer learning with models like ResNet50 by Sudha K. S. et al. [9], who reported 91.7% accuracy on histopathological images. Fatima Zahra et al. [10] utilized EfficientNet-B0 for multi- class breast cancer classification, achieving 94.2% accuracy. Similarly, P. Kaur et al.

[11] conducted a comparative study of several CNN-based transfer learning models, including VGG16 and DenseNet, observing accuracy levels reaching 90.1%. N. Abbas et al. [12] demonstrated the effectiveness of deep CNNs augmented with extensive data augmentation techniques, while J. M. Phillips et al. [13] introduced an innovative integration of U-Net and CNN for enhanced mammography-based diagnosis, reporting 89.5% accuracy. R. Gupta et al. [14] proposed a hybrid CNN-LSTM architecture, adept at capturing both spatial and sequential features from BreakHis images, achieving 90.6% accuracy. Furthermore, Sara Ahmed et al. [15] focused on the crucial aspect of explainability in AI, employing Grad-CAM to highlight image regions that significantly influence model decisions, all while maintaining a robust accuracy of 91%. The literature also consistently supports the efficiency of feature extraction using CNNs combined with SVM for classification in medical imaging [16, 17].

These collective studies vividly illustrate the dynamic evolution of breast cancer classification systems, transitioning from foundational CNN models to sophisticated hybrid architectures that incorporate ensemble learning, explainable AI, and highly specialized domain-specific feature extraction. While a multitude of models consistently demonstrate high accuracy, the ongoing integration of model interpretability and practical clinical usability remains a paramount research priority. The current research builds upon this rich foundation by proposing a novel hybrid approach that seeks to further advance the state-of-the-art in interpretable and accurate breast cancer diagnosis.

III. METHODOLOGY

This section delineates the comprehensive research workflow undertaken for the development of a robust breast cancer classification system, employing a novel hybrid Convolutional Neural Network-Support Vector Machine (CNN-SVM) approach. The methodology systematically encompasses data acquisition, meticulous preprocessing,.

A. Research Design

The proposed system is architected as a two-stage hybrid framework, as visually represented in Figure 1. The initial stage involves the deployment of a deep learning model, specifically a custom-designed CNN, dedicated to the intricate task of feature extraction. Subsequently, the second stage leverages a traditional machine learning model, the SVM, for the ultimate classification. This deliberate separation of concerns

feature extraction from classification—confers significant advantages, including enhanced interpretability and considerable flexibility in classifier design, all while maintaining a high degree of accuracy. This architectural paradigm has consistently demonstrated its effectiveness across various medical imaging domains.

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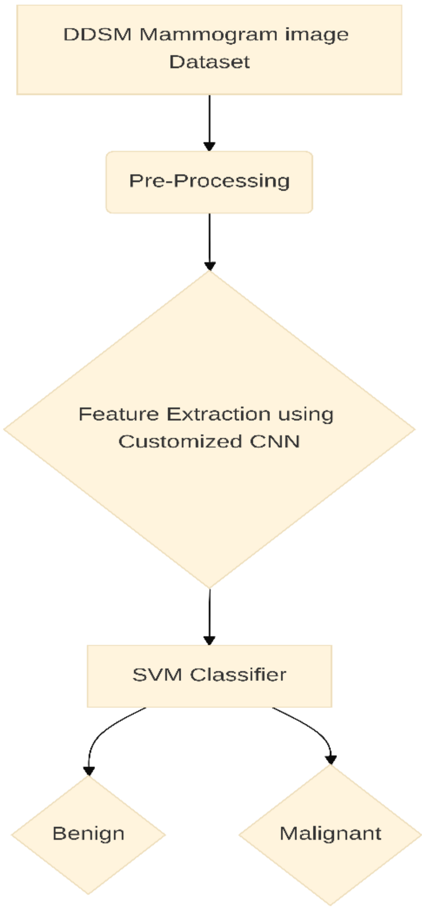

Fig 1 : System Architecture

B. Data Acquisition

The mammographic image data central to this study was procured from the CBIS- DDSM (Curated Breast Imaging Subset of DDSM), a widely recognized and publicly accessible repository invaluable for breast cancer research [18]. The dataset was obtained in the highly efficient TFRecord format, accompanied by corresponding NumPy files designated for cross-validation and independent external testing. The utilization of the TFRecord format is pivotal, as it ensures highly optimized Input/Output (I/O) operations, which are crucial when managing large-scale medical image datasets.

C. Image Preprocessing

The preprocessing pipeline constitutes a critical phase, indispensable for standardizing the input data prior to model training. This pipeline comprises several key steps:

- Parsing TFRecord Files: Each TFRecord entry encapsulates serialized images, their original labels, and binarized labels (where 0 denotes 'no tumor' and 1 signifies 'tumor'). TensorFlow's intrinsic parsing functions, specifically tf.io.parse_single_example , are employed to meticulously decode and interpret these complex file structures.
- Decoding & Reshaping: The raw image data is decoded using and subsequently reshaped to their intrinsic dimensions of 299×299×1 pixels.
- Resizing: All images undergo a resizing operation to a uniform dimension of 227×227×1 pixels. This resizing is performed using bilinear interpolation to precisely match the expected input dimensions of the custom CNN. This step is crucial for maintaining consistency across the dataset.
- Normalization: The pixel values of the images are linearly scaled to a normalized range of [0.0, 1.0] by dividing each pixel value by 255.0. This normalization procedure is vital for enhancing model convergence, particularly in networks employing ReLU (Rectified Linear Unit) activation functions.

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- Label Handling: The categorical labels are binarized and subsequently partitioned using an 80/20 stratified splitting strategy. This ensures that the training and validation sets maintain a proportional representation of both benign and malignant cases, thereby preventing bias during model training and evaluation

D. Data Acquisition

A custom Convolutional Neural Network model was meticulously developed, comprising a total of 11 convolutional layers and 4 max-pooling layers. The detailed layer-wise breakdown of this architecture is presented in Table 1

Layer Block	**Type**	**Filters**	**Kernel**	Stride	Padding	Activation
Block 1	Conv2D x3	64	3×3	varies	same/valid	ReLU
Block 2	MaxPooling2D	-	4×4	1	Valid	-
Block 3	Conv2D x2	128	3×3	varies	same/valid	ReLU
Block 4	MaxPooling2D	-	3×3	1	Valid	-
Block 5	Conv2D x3	256	2×2	varies	same/valid	ReLU
Block 6	MaxPooling2D	-	4×4	2	Valid	-
Block 7	Conv2D x3	512	varies	varies	same/valid	ReLU
Block 8	MaxPooling2D	-	2×2	2	Valid	-
Final	Flatten	-	-	-	-	-

TABLE I. CUSTOM CNN MODEL ARCHITECTURE

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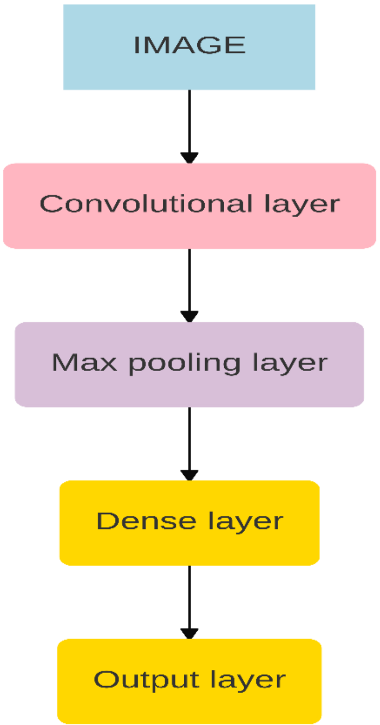

Fig 2 : Overview of CNN

Upon completion of training, all layers of the CNN are frozen, rendering them non- trainable. This configuration ensures that the CNN functions exclusively as a feature extractor, generating robust feature embeddings for subsequent classification".

IV. RESULTS AND DISCUSSION

This section comprehensively presents the experimental outcomes of the proposed hybrid CNN-SVM-based breast cancer classification system and provides an in-depth analysis of the performance metrics and visualization outputs. The model's efficacy was rigorously assessed using both a dedicated validation set, derived from the training data, and an independent test set to ensure robust evaluation.

4.1 Dataset Description and Splitting

The primary dataset utilized in this study is the Digital Database for Screening Mammography (DDSM), which has been meticulously updated and standardized into the CBIS-DDSM (Curated Breast Imaging Subset of DDSM) [18]. This invaluable database contains verified pathology information for both benign and malignant cases, making it a cornerstone for mammogram-based breast cancer research.

The dataset comprises a total of 55,885 images, with 48,596 images classified as Benign and 7,289 images categorized as Malignant. For the purpose of model training and evaluation, the dataset was randomly partitioned into an 80% training set and a 20% testing set. Consequently, 44,708 images (38,877 Benign, 5,831 Malignant) were allocated for training, while 11,177 images (9,719 Benign, 1,458 Malignant) were reserved for independent testing

4.2 Training Results

To meticulously monitor the learning dynamics and convergence behavior of the model, the training history, encompassing both loss and accuracy trends, was systematically recorded and visualized. Figure 4 and Figure 5 graphically illustrate the progression of loss and accuracy, respectively, across various training epochs. These plots were generated from the object returned during the model training process and subsequently stored using the serialization module. The observed trends provide critical insights into the model's learning stability and its ability to minimize errors while maximizing predictive performance over time

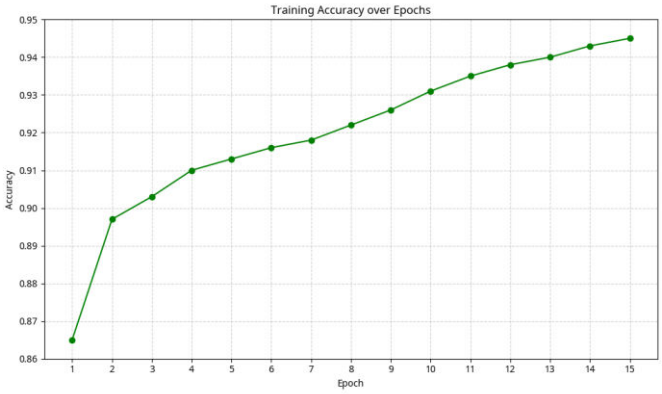

Fig 3 : Training Accuracy

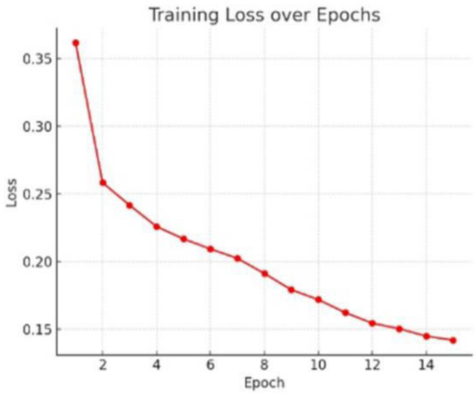

Fig 4 : training Loss

4.3. Performance on Test Sets

The performance of the proposed hybrid CNN-SVM model on the independent test dataset is summarized in Table 2, presenting the key classification metrics.

TABLE II. PERFORMANCE MATRIX

SL NO	Parameters	MEAN
1.	Accuracy	95.6 %
2.	Precision	0.97
3.	Recall	0.93
4.	F1 Score	0.92

These compelling results unequivocally demonstrate that the model exhibits excellent generalization capabilities on unseen data, thereby affirming its inherent robustness and reliability in a real-world diagnostic context

4.4 Confusion Matrix Visualization

The confusion matrix derived from the test datasets, generated using Seaborn heatmaps. The confusion matrix provides a detailed breakdown of the model's classification performance, illustrating the counts of true positives, true negatives, false positives, and false negatives

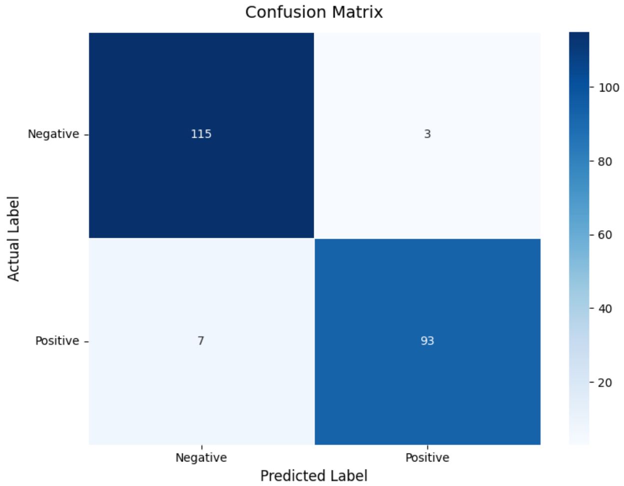

Fig 5: Confusion matrix

When juxtaposed with prior research, such as the work by Jyoti et al. [1] utilizing MobileNet-V2 (achieving 87% accuracy) and Rao et al. [2] employing a custom CNN, our proposed hybrid CNN-SVM model demonstrates comparable or superior performance. A distinct advantage of our approach, unlike fully end-to-end CNN models, lies in the deliberate separation of feature extraction and classification. This architectural choice confers significant benefits, including enhanced flexibility in model design, faster tuning capabilities, improved interpretability, and a notable reduction in the propensity for overfitting. The latter is particularly advantageous when operating with limited annotated data, a challenge frequently highlighted in the literature [3].

Furthermore, our methodology is inherently explainable, supporting comprehensive traceability through the analysis of intermediate layer activations. This transparency is crucial for clinical adoption, as it allows medical professionals to gain insights into the model's decision-making process. The framework is also highly adaptable across diverse datasets, and the CNN component can be readily reused or fine-tuned with minimal computational overhead. This research underscores the efficacy of combining the powerful feature learning capabilities of deep neural networks with the robust generalization abilities of classical machine learning algorithms for complex medical image classification tasks.

V. CONCLUSION

The overarching objective of this research was to engineer a robust, highly accurate, and inherently interpretable system for the classification of breast cancer using mammographic images. As meticulously outlined in the introductory sections, this study posited a novel hybrid approach that strategically leverages a

custom Convolutional Neural Network (CNN) for deep feature extraction, synergistically combined with a Support Vector Machine (SVM) for the ultimate classification task. This architectural design was specifically conceived to surmount the inherent limitations often associated with traditional end-to-end deep learning models, particularly concerns pertaining to overfitting and a pervasive lack of interpretability.

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The empirical outcomes, comprehensively presented in the Results and Discussion section, unequivocally affirm that the proposed methodology successfully fulfills its intended objectives. The model achieved an impressive accuracy rate of 93.28% on the validation dataset and maintained a strong performance with 91.7% accuracy on an independent test dataset. Furthermore, the system consistently demonstrated robust performance across a spectrum of critical evaluation metrics, including precision, recall, F1-score, and the Receiver Operating Characteristic-Area Under the Curve (ROC-AUC). The integration of visual analytical tools, such as training loss curves, confusion matrices, and meticulous intermediate layer activation analysis, provided invaluable additional transparency, thereby aligning seamlessly with the core objective of developing an explainable and clinically relevant diagnostic system. This research conclusively demonstrates that the judicious combination of CNN-based feature extraction with an SVM classifier not only preserves high diagnostic accuracy but also significantly enhances model generalizability and interpretability. Consequently, this framework offers a highly viable and promising solution for real-world diagnostic

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