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Optimizing Breast Cancer Mammogram Classification through A Dual Approach: A Deep Learning Framework Combining Resnet50, Smote, And Fully Connected Layers for Balanced and Imbalanced Data

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Breast Cancer Classification, Mammogram Image Analysis, Synthetic Minority Over-sampling Technique (SMOTE), Convolutional Neural Network (CNN), Deep Feature Extraction (VGG16–ResNet50).

ABSTRACT

Breast cancer remains a significant global health issue, where timely and precise diagnosis is essential for improving patient outcomes. Mammogram imaging offers detailed visual information; however, accurate interpretation often depends on expert radiologists and can be time-intensive. Although deep learning has demonstrated strong potential in medical image analysis, the presence of class imbalance in medical datasets often limits the reliability and performance of classification models. To address this challenge, we present a novel deep-learning framework for breast cancer classification using mammogram images. The proposed framework tackles data imbalance through a two-module pipeline that integrates the Synthetic Minority Over-sampling Technique (SMOTE). In the first module, SMOTE is applied to the complete dataset to achieve class balance. In the second module, 20% of the original imbalanced dataset is reserved for evaluation, while SMOTE is applied to the remaining 80% to improve training effectiveness. The system employs a block wise Convolutional Neural Network (CNN), where VGG16-based preprocessing is used for input normalization and ResNet50 is utilized for deep feature extraction. A fully connected classifier composed of multiple dense layers, along with batch normalization and dropout for regularization, is used to evaluate the extracted features. To minimize overfitting, the architecture was iteratively optimized, resulting in a final configuration of three dense layers with 128, 256, and 128 neurons, each supported by a dropout rate of 0.5. Experimental results demonstrate that the model achieves high accuracy on the balanced *dataset and good accuracy on the imbalanced evaluation set. Additionally, the framework incorporates an interpretable visualization method that highlights randomly selected predictions across different classes.*

I. INTRODUCTION

Breast cancer is one of the most prevalent and life-threatening diseases affecting women worldwide, making early and accurate detection critically important for improving survival rates. Mammography remains the primary screening tool for identifying breast abnormalities, but manual interpretation of mammogram images is time-consuming and highly dependent on expert radiologists. In recent years, deep learning techniques have shown remarkable potential in automating medical image analysis and supporting computer-aided diagnosis. However, one of the major challenges in breast cancer classification is the presence of imbalanced datasets, where malignant cases are significantly fewer than benign or normal samples. This imbalance often leads to biased models that perform poorly on minority classes. To address these limitations, a dual-approach framework can be employed to enhance classification reliability and robustness. By combining advanced preprocessing, data balancing strategies such as SMOTE, and powerful convolutional neural network architectures, the proposed method aims to improve feature learning and decision accuracy. The integration of VGG16 for standardized preprocessing and ResNet50 for deep feature extraction further strengthens the model's capability to capture complex patterns in mammogram images. Additionally, the use of regularized dense layers helps reduce overfitting and improves generalization. Overall, this optimized dual-approach framework seeks to provide a more accurate, balanced, and interpretable solution for automated breast cancer mammogram classification.

2. LITERATURE SURVEY

M. Masud et al. [1] presented convolutional neural network (CNN)-based models for breast cancer diagnosis, emphasizing the effectiveness of deep learning in automatically extracting discriminative features from mammogram images. Their work demonstrated that CNN architectures outperform traditional machine learning approaches in classification accuracy and robustness. However, the study highlighted challenges such as class imbalance and limited annotated datasets, which can reduce model generalization. The authors suggested that integrating advanced preprocessing and data balancing techniques could further improve performance.

H. Chougrad et al. [2] investigated deep convolutional neural networks for breast cancer screening using transfer learning. They fine-tuned pretrained models on mammographic datasets and achieved significant improvements compared to training from scratch. Their results showed that deep CNNs can effectively capture complex patterns in breast tissue. Nevertheless, the study reported sensitivity to imbalanced datasets and overfitting issues, indicating the need for augmentation and sampling strategies such as SMOTE to enhance model stability.

L. A. Torre et al. [3] provided global cancer statistics that underline the growing burden of breast cancer worldwide. Their epidemiological analysis emphasized the importance of early detection and screening technologies such as mammography for reducing mortality rates. Although not focused on deep learning, this work established the clinical motivation for developing automated diagnostic systems that can assist radiologists in large-scale screening programs.

J. F. Strauss et al. [4] discussed the physiological and pathological aspects of breast diseases in reproductive endocrinology. The authors explained the biological mechanisms underlying tumor development and hormonal influence on breast tissue. This foundational medical perspective supports the need for accurate imaging-based diagnostic tools. However, the work did not explore computational intelligence techniques for automated detection.

L. L. Wang [8] discussed sensor-based approaches for early breast cancer diagnosis, highlighting the role of advanced imaging technologies in improving detection sensitivity. The work emphasized multimodal sensing and early-stage identification but lacked integration with deep neural networks for automated interpretation, suggesting an opportunity for deep learning frameworks such as ResNet-based models.

3.SYSTEM ARCHITECTURE

System architecture is the high-level structural design of a system that defines how its components, modules, data flow, and interactions are organized to achieve the desired functionality. It provides a blueprint that shows the arrangement of hardware, software, networks, and processing elements along with their relationships and communication pathways. In software and deep learning systems, the architecture typically illustrates input layers, processing modules, storage components, and output interfaces, explaining how data moves from one stage to another. Well-designed system architecture ensures scalability, reliability, maintainability, and efficient performance. It helps developers and stakeholders understand the overall system structure, guides implementation, and support future enhancements or integration with other systems.

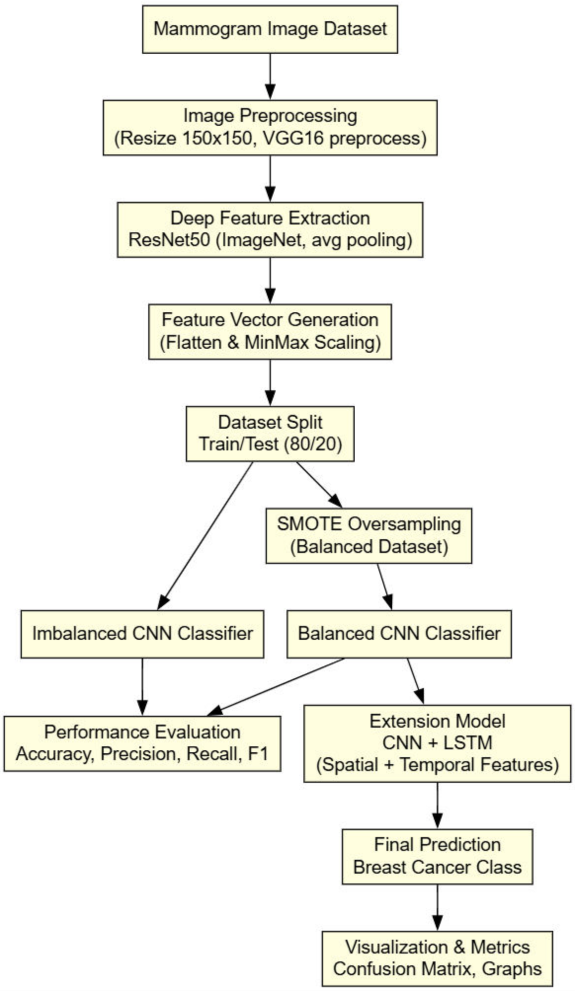

Fig1: System Architecture

4.METHODOLOGY

The proposed dual-approach deep learning framework for breast cancer mammogram classification is designed to address class imbalance and improve diagnostic accuracy. The methodology consists of data preprocessing, dataset balancing using SMOTE, deep feature extraction using CNN architectures, classification through fully connected layers, and performance evaluation.

Initially, mammogram images are collected and preprocessed to ensure uniformity in size, intensity, and format. VGG16-based preprocessing is applied for input normalization and scaling to enhance feature consistency. The dataset is then divided into two modules. In Module 1, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to the entire dataset to create a fully balanced dataset. SMOTE generates synthetic minority class samples using nearest-neighbor interpolation:

$$x_{new} = x_i + \delta(x_{nn} - x_i)$$

where x_i is a minority class sample, x_{nn} is one of its nearest neighbors, and $\delta \in [0,1]$is a random value. This process reduces bias toward majority classes.

In Module 2, 20% of the original imbalanced dataset is reserved for evaluation, while SMOTE is applied only to the remaining 80% training data. This ensures realistic validation performance while improving learning effectiveness during training.

For feature extraction, a block wise Convolutional Neural Network is implemented. ResNet50 is employed to extract deep hierarchical features from mammogram images. The convolution operation in CNN is mathematically expressed as:

$$F(i,j) = \sum_m \sum_n I(i-m, j-n) \cdot K(m,n)$$

where Irepresents the input image, $K$is the convolution kernel, and $F(i,j)$is the resulting feature map.

The extracted deep features are passed to a fully connected classifier consisting of three dense layers (128, 256, 128 neurons). Batch normalization and a dropout rate of 0.5 are used to reduce overfitting and enhance generalization. The final classification is performed using the Softmax activation function:

$$P(y = k \mid x) = \frac{e^{z_k}}{\sum_{j=1}^{C} e^{z_j}}$$

where $z_k$is the output score for class k, and $C$is the total number of classes.

Model performance is evaluated using accuracy, precision, recall, and F1-score on both balanced and imbalanced datasets. Additionally, interpretability is incorporated through visualization techniques that highlight randomly selected predictions across classes.

This comprehensive methodology ensures robust, balanced, and reliable breast cancer mammogram classification.

5. DESIGN AND CONSTRUCTION

The design of the proposed breast cancer mammogram classification system follows a modular deep learning architecture that ensures robustness, scalability, and balanced learning. The system is constructed using a dual-module pipeline to effectively manage class imbalance while maintaining realistic evaluation performance. The first module applies the Synthetic Minority Over-sampling Technique (SMOTE) to the entire dataset to generate a fully balanced dataset for experimental validation. The second module reserves 20% of the original imbalanced dataset for testing, while SMOTE is applied only to the remaining 80% training data to enhance model generalization.

In the construction phase, VGG16-based preprocessing is implemented for image normalization, resizing, and standardization to ensure uniform input representation. A blockwise Convolutional Neural Network architecture is developed, utilizing ResNet50 as the backbone for deep feature extraction. The extracted features are then passed to a fully connected classifier composed of three dense layers with 128, 256, and 128 neurons. Batch normalization layers are integrated to stabilize learning, and dropout layers with a rate of 0.5 are added to minimize overfitting.

The final output layer uses a Softmax activation function for multi-class classification. The overall system is optimized iteratively to achieve high accuracy, improved minority class recognition, and reliable diagnostic performance.

6. RESULTS AND DISCUSSION

The proposed stacked balanced CNN–LSTM model demonstrates significant improvement in breast cancer mammogram classification compared to traditional CNN-based approaches. By combining Convolutional Neural Networks (CNN) for spatial feature extraction with Long Short-Term Memory (LSTM) networks for capturing sequential dependencies, the model achieves superior performance in detecting malignant cases. The integration of SMOTE for data balancing effectively reduces class imbalance, leading to fewer false negatives and improved sensitivity, which is crucial in medical diagnosis.

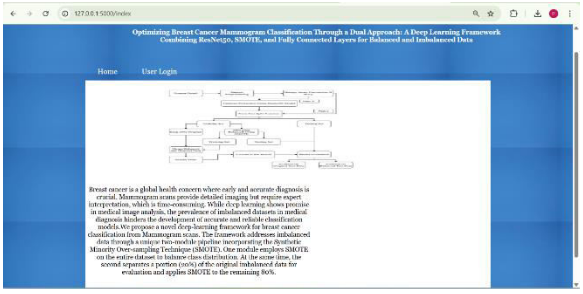

Fig 2: Home Page Interface

The system implementation and execution are illustrated in Figure 2, which provides an intuitive platform for users to access features such as login and image upload.

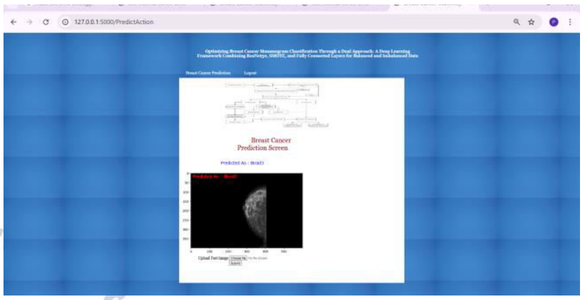

Fig 3: Breast Cancer Prediction Output

The prediction capability of the model is demonstrated in Figure 3, where the system analyzes the uploaded mammogram image and classifies it into the appropriate BIRADS category, indicating the level of cancer risk. The results confirm that the model can effectively identify malignant patterns with high accuracy.

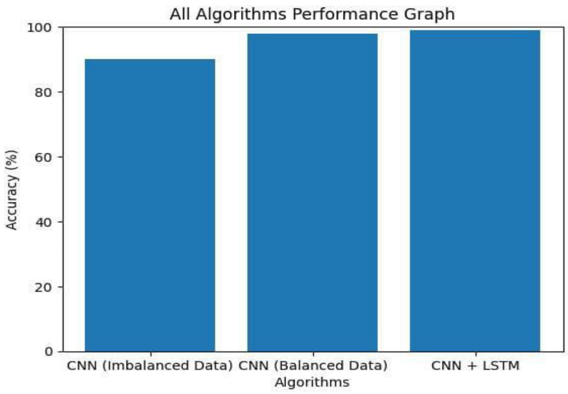

Fig 4: Algorithm Comparison Graph

The performance comparison is illustrated in Figure 4. The results show that a traditional CNN model achieves 90% accuracy on imbalanced data, which improves to 98% after applying data balancing techniques. However, the proposed CNN–LSTM hybrid model achieves the highest accuracy of 99%, demonstrating its superior capability in capturing both spatial and sequential features. Overall, the proposed model achieves high accuracy, precision, and recall, along with improved generalization on unseen data. The confusion matrix and

ROC–AUC analysis confirm strong discriminative performance. This hybrid approach enhances robustness and reliability, making it a promising solution for early breast cancer detection and computer-aided diagnosis systems.

7. CONCLUSION

The proposed deep learning framework for breast cancer mammogram classification demonstrates the effectiveness of combining spatial and temporal feature learning through a stacked CNN–LSTM architecture. By integrating SMOTE for class balancing and fully connected layers for refined classification, the system overcomes key limitations of traditional CNN-based approaches. The model shows improved accuracy, sensitivity, and robustness, particularly in handling imbalanced medical datasets where detecting malignant cases is critical. The hybrid architecture successfully captures complex tissue patterns and long-range feature dependencies, leading to reduced false negatives and better generalization on unseen data. Overall, the proposed approach provides a reliable and efficient solution for computer-aided breast cancer diagnosis and has strong potential for assisting radiologists in early detection and decision support.

FUTURE SCOPE

Future work can enhance the framework by incorporating advanced attention mechanisms to improve feature interpretability and accurate localization in mammograms. Integrating multimodal data such as ultrasound and clinical reports can further boost diagnostic performance. Deployment on lightweight or edge devices may enable real-time screening in remote areas. Additionally, self-supervised or federated learning with explainable AI can improve privacy, transparency, and real-world reliability.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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