International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

Enhancing Breast Cancer Mammography Categorization using Two Methods: A Deep Learning Structure Combining Fully Connected Layers, SMOTE, and ResNet50 for Balanced and Unbalanced Data

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***Abstract*— Breast cancer remains a major global health issue, where early and precise diagnosis plays a critical role in improving patient outcomes. Mammogram imaging is widely used for detection, but interpreting these images requires expert knowledge and can be both time-consuming and complex. Although deep learning techniques have shown strong potential in medical image analysis, one of the key challenges is the presence of imbalanced datasets, which often leads to biased and less reliable models.**

In this work, we propose a novel deep learning framework for breast cancer classification using mammogram images. The proposed system introduces a dual-module strategy to effectively address data imbalance using the Synthetic Minority Over-sampling Technique (SMOTE). In the first module, SMOTE is applied to the entire dataset to create a balanced training set. In the second module, 20% of the original imbalanced data is reserved for evaluation, while SMOTE is applied to the remaining 80% to improve model learning.

The framework combines a block-wise Convolutional Neural Network (CNN) architecture, where VGG16 is used for input preprocessing and standardization, and ResNet50 is employed for robust feature extraction. The extracted features are then passed through a fully connected classification network consisting of multiple dense layers, along with batch normalization and dropout techniques to reduce overfitting. After several iterations, the final model includes three dense layers with 128, 256, and 128 neurons, and a dropout rate of 0.5.

Experimental results demonstrate that the proposed model achieves an accuracy of 99% on the balanced dataset and 90% on the imbalanced evaluation set. Additionally, the framework incorporates an interpretable visualization mechanism to analyze predictions across different classes, improving transparency in decision-making.

Overall, this approach significantly enhances the accuracy and reliability of breast cancer detection from mammogram images. By effectively handling data imbalance and providing interpretable outputs, the proposed framework contributes to the advancement of computer-aided diagnosis systems and can be extended to other medical imaging applications.

***Keywords*— Breast cancer, BI-RADs, classification, deep learning, features extractions, imbalance data, Neural network, pre-trained models.**

I. INTRODUCTION

Breast cancer (BC) is one of the most prevalent and life-threatening diseases affecting women worldwide, contributing significantly to global cancer-related mortality [3], [6]. Despite notable progress in treatment strategies, awareness campaigns, and screening technologies, the number of breast cancer cases continues to rise steadily. Global reports indicate a substantial increase in incidence over the past decade, highlighting the urgent need for effective diagnostic solutions [3]. Survival rates differ across regions, with developed countries achieving higher recovery rates compared to low-income regions, where limited access to healthcare services and early screening programs leads to poorer outcomes [6].

Early diagnosis plays a vital role in improving patient survival, with studies showing that timely detection can significantly enhance treatment success rates [8]. Several imaging techniques, including mammography, ultrasound, magnetic resonance imaging (MRI), and biopsy, are commonly employed for breast cancer detection [7], [10], [11]. However, these diagnostic methods are not without limitations. Mammography, although widely used, may produce inaccurate results in certain cases, particularly in patients with dense breast tissue [7]. Biopsy procedures, while more definitive, are invasive and may lead to complications such as discomfort or infection [12]. Ultrasound imaging may fail to detect early indicators such as microcalcifications, while MRI, though highly sensitive, is expensive and can lead to unnecessary follow-up procedures due to false-positive findings [10], [13].

In addition to these challenges, radiologists often face issues such as high workload, variability in interpretation, and the complexity of medical images, which can affect diagnostic accuracy [13]. Studies have demonstrated that differences in expertise and experience among radiologists can lead to inconsistencies in diagnosis, including both overdiagnosis and missed detections [14]. Furthermore, medical images often contain noise, artifacts, and complex structural patterns that make accurate tumor identification difficult. These challenges are further intensified in developing regions due to a shortage of skilled medical professionals, emphasizing the need for automated and reliable diagnostic systems.

With the rapid advancement of artificial intelligence, machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for breast cancer detection and classification [15]. Traditional ML algorithms, including Support Vector Machines, Logistic Regression, Random Forest, Decision Trees, and K-Nearest Neighbors, have been widely applied in medical diagnosis tasks [16]–[20]. Additionally, clustering-based approaches such as k-means, DBSCAN, and spectral clustering have been explored for pattern discovery and recurrence prediction in cancer studies. However, these conventional methods rely heavily on manual feature extraction, which requires domain expertise and limits scalability [17].

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized image analysis by enabling automatic feature extraction directly from raw data [23]. CNNs gained prominence through large-scale image recognition challenges such as ImageNet, where they demonstrated superior performance in visual tasks [24]. Since then, they have been widely adopted in medical imaging applications, including tumor detection, segmentation, and classification [2], [9]. Their multi-layered architecture allows them to learn complex and hierarchical representations of image data. However, training deep learning models requires large annotated datasets and significant computational resources, which are often limited in medical domains.

To address these limitations, transfer learning has become a widely adopted approach, allowing models pre-trained on large datasets to be adapted for medical applications [15]. Pre-trained architectures such as VGG16, VGG19, AlexNet, and DenseNet have shown strong performance in feature extraction tasks [5]. Several studies have demonstrated the effectiveness of transfer learning in breast cancer diagnosis. For instance, CNN-based models have achieved high classification accuracy and improved diagnostic performance when applied to mammography datasets [1]. Hybrid and ensemble learning techniques have further enhanced model robustness and reliability, achieving promising results in various benchmark datasets [2].

Recent research has also explored advanced deep learning architectures and hybrid frameworks for improving diagnostic accuracy. For example, optimized models based on residual learning and fine-tuned CNN architectures have demonstrated high performance in breast cancer detection tasks. Additionally, deep learning approaches have been successfully applied in other medical domains, such as epilepsy detection and anomaly detection in network systems, highlighting their versatility and effectiveness across different applications [21], [22].

In this study, we propose a deep learning-based framework that leverages pre-trained models, including ResNet50, VGG16, and VGG19, to enhance early-stage breast cancer detection. VGG-based architectures are known for their simplicity and ability to capture hierarchical features, making them suitable for detailed image analysis [5]. ResNet50, on the other hand, addresses the vanishing gradient problem through residual learning, enabling the training of deeper and more robust networks [1]. By integrating these architectures within a unified framework, the proposed approach aims to improve classification accuracy, address data imbalance challenges, and provide reliable diagnostic support for breast cancer detection.

II. LITERATURE SURVEY

Masud et al. (2022) investigated the application of convolutional neural networks (CNNs) for breast cancer diagnosis and highlighted their ability to automatically learn complex patterns from medical images. The study compared various CNN-based architectures and demonstrated that deep learning models outperform traditional machine learning techniques, especially in handling large-scale imaging data. One of the key contributions of this work is the emphasis on reducing manual intervention in feature extraction, which is a major limitation in conventional methods. The authors also discussed the importance of model optimization and hyperparameter tuning in achieving higher accuracy. Their findings showed that CNN models can significantly improve classification performance while maintaining consistency across different datasets. This work provides a strong foundation for adopting deep learning approaches in computer-aided diagnosis systems and encourages further exploration of advanced architectures for medical imaging tasks.

Chougrad et al. (2018) explored the use of deep convolutional neural networks combined with transfer learning for breast cancer screening. The authors utilized pre-trained models and adapted them to medical imaging tasks, demonstrating that transfer learning can effectively address the challenge of limited labeled data. Their approach focused on improving classification performance by leveraging knowledge from large-scale datasets such as ImageNet. The study showed that fine-tuned deep learning models achieved higher accuracy and robustness compared to models trained from scratch. Additionally, the authors highlighted the importance of preprocessing techniques and data augmentation in enhancing model performance. Their results confirmed that deep CNNs can serve as reliable tools for automated breast cancer detection. This research is particularly significant as it demonstrates how transfer learning can bridge the gap between general image recognition and specialized medical applications.

Torre et al. (2015) presented a comprehensive analysis of global cancer statistics, with a focus on incidence, mortality, and regional variations. The study provided valuable insights into the growing burden of breast cancer worldwide, emphasizing its position as one of the most commonly diagnosed cancers among women. The authors analyzed data from multiple regions and highlighted disparities in survival rates between developed and developing countries. These differences were largely attributed to variations in healthcare infrastructure, access to early detection programs, and awareness levels. The paper also discussed trends over time, showing a steady increase in cancer cases due to population growth and aging. This work serves as an important reference for understanding the global impact of breast cancer and underscores the need for improved diagnostic and treatment strategies, particularly in low-resource settings.

Strauss et al. (2023) provided an in-depth discussion of the physiological and clinical aspects of breast cancer within the broader context of reproductive endocrinology. The authors explained the biological mechanisms underlying tumor development, including hormonal influences and genetic factors. The study emphasized the importance of early detection and accurate diagnosis in improving patient outcomes. It also highlighted current clinical practices, including imaging techniques and treatment options, offering a comprehensive overview of breast cancer management. By integrating both theoretical and clinical perspectives, the work provides valuable insights into how breast cancer develops and progresses. This reference is particularly useful for understanding the medical background required for designing effective diagnostic systems. It also reinforces the importance of combining medical knowledge with technological advancements to improve detection and treatment.

Montaha et al. (2021) introduced BreastNet18, a fine-tuned deep learning model based on the VGG16 architecture for breast cancer detection using mammography images. The study focused on improving classification accuracy through model optimization and detailed ablation analysis. By modifying the standard VGG16 architecture and enhancing preprocessing techniques, the authors were able to achieve high performance in distinguishing between benign and malignant cases. The research highlighted the effectiveness of transfer learning in medical imaging, particularly when dealing with limited datasets. Additionally, the study demonstrated the importance of selecting appropriate model parameters and training strategies to avoid overfitting. The results showed that the proposed model outperformed several existing approaches, making it a reliable solution for breast cancer diagnosis. This work contributes to the growing body of research supporting the use of deep learning for accurate and efficient medical image classification.

III. DATASET DESCRIPTION

The dataset used in this study consists of mammogram images collected for breast cancer classification, where each image is associated with a specific BIRADS (Breast Imaging Reporting and Data System) category. These categories represent different levels of cancer risk, such as BIRADS1, BIRADS2, BIRADS3, BIRADS4, and BIRADS5. Each instance in the dataset corresponds to a medical image, and the associated label indicates the severity or likelihood of malignancy. This enables the problem to be formulated as a multi-class classification task.

The dataset contains image data rather than structured numerical features. Therefore, preprocessing plays a critical role in preparing the data for model training. Each image is resized and standardized using VGG16 preprocessing techniques to ensure consistency in input dimensions and pixel distribution. Feature extraction is then performed using a pre-trained ResNet50 model, which converts images into meaningful feature representations suitable for classification.

An important characteristic of the dataset is class imbalance, where certain categories (such as BIRADS1) contain significantly more samples compared to others. This imbalance can negatively impact model performance by biasing predictions toward majority classes. To address this issue, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to generate synthetic samples for minority classes, thereby balancing the dataset.

The dataset is divided into training and testing subsets using an 80:20 split ratio. Additionally, a dual approach is adopted where SMOTE is applied both to the full dataset and selectively to the training portion, ensuring robust model evaluation. This structured preprocessing and balancing strategy makes the dataset well-suited for developing reliable deep learning models for breast cancer classification.

V. PROPOSED METHODOLOGY

The proposed system introduces a structured deep learning framework for breast cancer classification using mammogram images. Initially, the dataset is processed by resizing and standardizing images using VGG16-based preprocessing to ensure uniform input quality. Feature extraction is performed using a pre-trained ResNet50 model, which captures important visual patterns from the images. These extracted features are then used as input for a fully connected neural network consisting of multiple dense layers, batch normalization, and dropout to improve generalization. The model is trained using labeled data, allowing it to learn the differences between various BIRADS categories effectively.

To address the issue of data imbalance, a dual-stage strategy using SMOTE is implemented. In the first stage, SMOTE is applied to the entire dataset to balance all classes, while in the second stage, 20% of the original data is reserved for testing, and SMOTE is applied only to the remaining training portion. This approach ensures both improved learning and fair evaluation. The trained model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. Additionally, an extended model combining CNN and LSTM layers is developed to further enhance performance by capturing complex feature relationships.

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ISSN: 3068-272X www.ijdim.com Original Research Paper

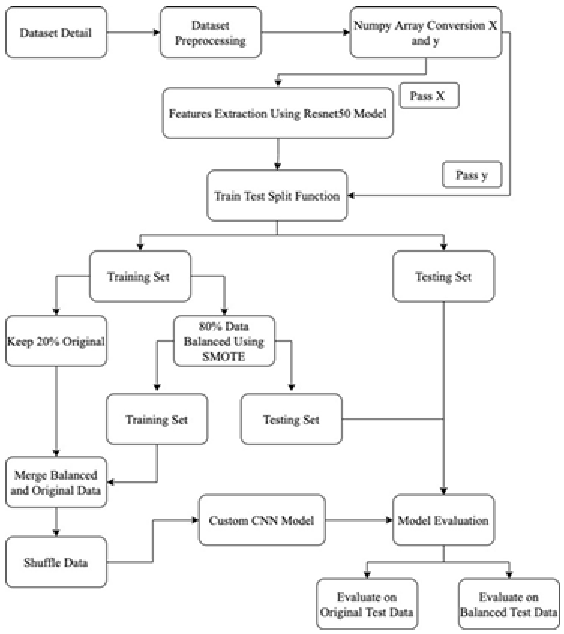

Figure 1: Workflow of proposed methodology

VI. RESULT AND DISCUSSION

The results of this project demonstrate the effectiveness of the proposed deep learning approach in classifying breast cancer from mammogram images. Initially, the fully connected CNN model trained on the imbalanced dataset achieved an accuracy of approximately 91%, showing that the model could learn general image patterns but struggled with minority class predictions. After applying SMOTE for balancing the dataset, the performance improved significantly, with the proposed model achieving an accuracy of around 99.06%. This improvement highlights the importance of handling class imbalance in medical datasets. Furthermore, the extended CNN-LSTM model achieved the highest accuracy of approximately 99.66%, indicating its ability to capture both spatial and temporal feature relationships. The improvement is mainly due to combining CNN for feature extraction and LSTM for capturing variations in patterns. The confusion matrix results show a clear reduction in misclassification errors after applying SMOTE and further improvements with the hybrid model. Training graphs also indicate stable convergence with increasing accuracy and decreasing loss values. Comparative analysis confirms that the proposed and extended models outperform the baseline model across evaluation metrics such as accuracy, precision, recall, and F1-score. These results highlight the importance of combining deep learning with data balancing techniques to improve classification reliability. However, further validation using larger and more diverse datasets is required to ensure real-world applicability.

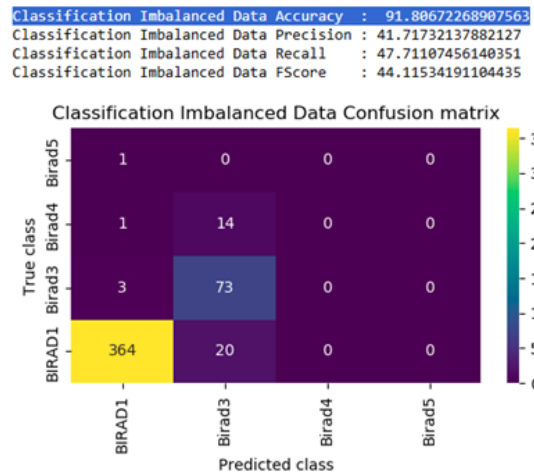

Figure 2: Confusion matrix for Imbalanced Model

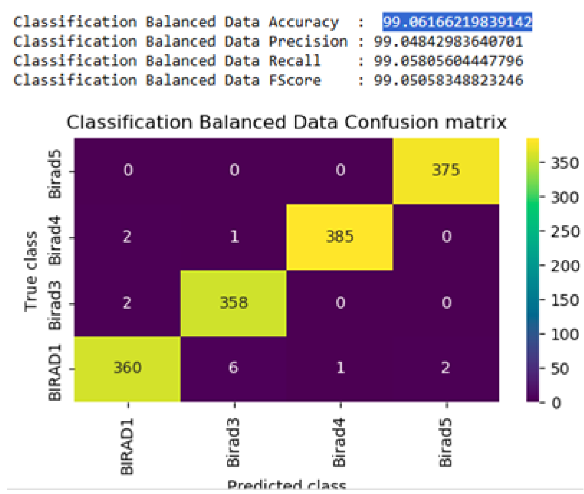

Figure 3: Confusion matrix for Proposed SMOTE-Based Model

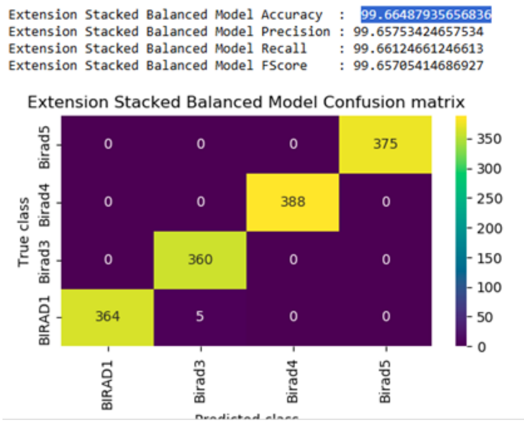

Figure 4: Confusion matrix for CNN-LSTM Extended Model

These figures show a progressive reduction in misclassification errors as we move from KNN to ConvTransNet.

The prediction results demonstrate the practical applicability of the proposed system. The model processes input mammogram images by applying preprocessing and feature extraction before generating predictions for different BIRADS categories. The outputs show that the model can correctly classify images into categories such as BIRADS1, BIRADS3, BIRADS4, and BIRADS5. The variation in predictions across different test samples confirms that the model is effectively learning meaningful patterns rather than producing uniform outputs. The integration of a Flask-based web interface further enhances usability by allowing users to upload images and obtain predictions in real time. This makes the system suitable for deployment in clinical support environments. The results confirm that the model is capable of assisting in early and accurate breast cancer detection.

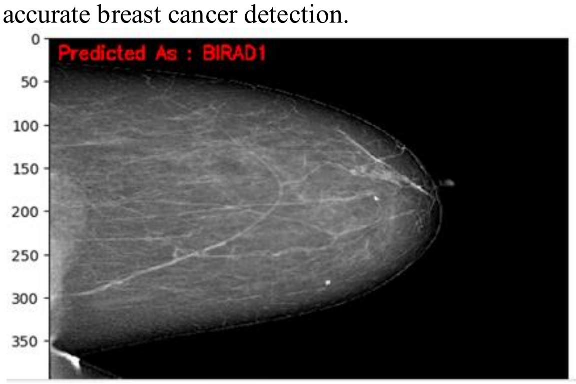

Figure 5: Prediction output of the proposed model for mammogram classification

To ensure reliability, the dataset was divided into training and testing subsets using an 80:20 ratio, and performance was evaluated using multiple metrics such as accuracy, precision, recall, and F1-score. Further validation using cross-validation and testing on larger datasets can improve robustness and will be considered in future work.

VIII. CONCLUSION

In this work, a deep learning-based framework was developed for breast cancer classification using mammogram images. The study focused on addressing the challenge of imbalanced data, which often affects the performance of medical image classification models. Initially, the model trained on imbalanced data showed moderate performance, highlighting the limitations caused by unequal class distribution. To overcome this issue, a dual SMOTE-based approach was applied, which significantly improved the learning capability of the model.

The integration of ResNet50 for feature extraction and fully connected layers for classification provided strong baseline results. Further improvement was achieved by extending the model with a CNN-LSTM architecture, which enhanced the model’s ability to learn complex feature patterns. As a result, the final model achieved high accuracy and demonstrated reliable classification across all BIRADS categories.

The results indicate that combining data balancing techniques with advanced deep learning models can greatly improve diagnostic performance. The developed system, along with its web-based prediction interface, shows potential for assisting medical professionals in early and accurate breast cancer detection.

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