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# Implementation of a Hybrid MobileNetV2 Model for Early Detection of Breast Cancer Based on Mammography Images from RSUP Dr. M. Djamil Padang

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**Abstract**

Breast cancer poses a significant health risk to women; however, early detection through mammographic imaging continues to face challenges in achieving high diagnostic accuracy using conventional diagnostic methods. Deep learning offers a solution for improving the accuracy of medical image classification; however, a single model remains limited, so a hybrid approach combining two methods is needed to achieve optimal performance. This study aims to develop and evaluate a Hybrid Deep Learning model that combines MobileNetV2 and XGBoost to detect and classify breast cancer based on mammography images. The research method begins with image preprocessing consisting of resizing, normalization, and augmentation, after which the dataset is split into training and testing data with an 80:20 ratio. MobileNetV2 is used as a feature extractor, producing a 1,280-dimensional feature vector, which is then classified by XGBoost into three classes: normal, benign, and malignant. The dataset consists of 224x224-pixel breast cancer mammography images sourced from RSUP Dr. M. Djamil Padang and the Kaggle platform. The test results show that the Hybrid MobileNetV2 and XGBoost model achieved an accuracy of 75%, a weighted precision of 77%, a weighted recall of 75%, and a weighted F1-score of 74%. The model performed best on the normal class, while the benign class experienced misclassification due to visual similarity with other classes. This study is expected to serve as a foundation for developing an accurate and efficient digital image-based breast cancer detection system to support medical personnel in clinical decision-making.

Keywords: breast cancer, hybrid deep learning, MobileNetV2, XGBoost, mammography.

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## 1. Introduction

Breast cancer is one of the non-communicable diseases that poses a global health threat, in which breast cells grow abnormally and can spread to the lymph nodes or other organs [1]. This disease is recorded as the second most common cancer in the world and one of the cancer types that most frequently affects women [2]. Globally, breast cancer is diagnosed in 2.1 million new cases every year and causes more than 626,679 deaths [3]. In Indonesia, breast cancer is the type of cancer with the highest number of cases, namely 58,256 cases or 16.7% of the total national cancer cases [4], while 2020 Globocan data recorded more than 68,858 new cases with more than 22 thousand deaths [5]. More than 80% of new breast cancer cases are detected at an advanced stage due to low public awareness and the lack of early detection programs, so a more sensitive and specific diagnostic method is needed to differentiate between benign and malignant cancer in order to avoid errors in patient management [6].

Various previous studies have developed artificial intelligence models to support more accurate breast cancer detection. Arianda et al. applied a deep learning-based Artificial Neural Network (ANN) to the Haberman dataset and achieved a prediction accuracy of up to 100% [7]. Another study by Mahesa et al. used a CNN ensemble approach combining MobileNet, MobileNetV2, and VGG16 for the classification of breast cancer histology images, obtaining an F1-score of 0.8682 and a balanced accuracy of 0.8689 [8]. Arwoko and Ariyani applied the MobileNet, MobileNetV2, and Xception architectures to breast cancer ultrasound images and obtained an F1-score of 89% [9]. Another study by Adzkia and Arifin compared transfer learning-based CNN architectures, namely MobileNetV2, ResNet50, and VGG16, on the BreastMNIST dataset, in which MobileNetV2 achieved an accuracy of 91.14% and an AUC of 0.9607 [10]. These findings indicate that a single model still has room for performance improvement, thereby encouraging the development of hybrid approaches that combine more than one method [11].

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Generally, deep learning constitutes an artificial intelligence subfield that leverages layered neural network architectures to automatically identify patterns from vast amounts of data [12]. The ability of deep learning to recognize complex patterns in data such as images and sound makes it highly relevant for medical image analysis, including breast cancer detection [13]. One widely used Convolutional Neural Network (CNN) architecture is MobileNetV2, which is designed to overcome the limitations of conventional CNNs that require substantial computational power [14]. MobileNetV2 has proven to deliver high image classification performance with a lighter computational load compared to conventional CNNs[15], making it well suited for medical image analysis because it can operate quickly and accurately [16].

On the other hand, XGBoost is a boosting-based classification algorithm known for its strong capability in handling complex data and improving classification accuracy [17]. The combination of a deep learning model as a feature extractor and XGBoost as a classifier is referred to as a hybrid approach, which allows the strengths of each method to complement one another to produce more optimal performance [11]. This approach has been proven to significantly improve classification accuracy compared to the use of a single model [18], while also providing better stability when dealing with highly varied data [19]. Hybrid models based on MobileNetV2 and XGBoost have been widely used specifically in breast cancer classification because they can improve accuracy, accelerate computation, and reduce the risk of overfitting on medical image data [20].

Several previous studies have tested the effectiveness of combining MobileNetV2 with other methods to improve classification performance. Ismail et al. developed a hybrid model combining MobileNetV2 with a Convolutional Block Attention Module (CBAM) and VGG16 for skin cancer classification, in which the addition of CBAM was shown to improve the quality of important features, achieving an accuracy of 89% [21]. Rozi et al. applied MobileNetV2 with optimizer adjustments for Android-based melanoma skin cancer detection and obtained an accuracy of 93.09% with a precision of 98% [22]. Widodo et al. combined SMOTE and ADASYN techniques with Random Forest and XGBoost to address imbalanced data in cervical cancer detection, resulting in a recall of 0.87 and an AUC of 0.94 [23]. Andryan et al. compared XGBoost with Support Vector Machine (SVM) on the Wisconsin Breast Cancer dataset and found that XGBoost outperformed SVM, achieving an accuracy of 95.12% compared to 90.24% for SVM [24]. These findings reinforce the basis for using MobileNetV2 and XGBoost as a hybrid method combination in this study.

Based on the above description, this study develops a hybrid deep learning model that combines MobileNetV2 as a feature extractor and XGBoost as a classification algorithm to detect breast cancer. The data used consist of mammography images sourced from RSUP Dr. M. Djamil Padang, one of the main referral hospitals in West Sumatra with representative facilities and clinical data to support research in the health sector. The research stages include image preprocessing consisting of resizing, normalization, and augmentation to improve the quality and variation of the data before it is processed by the deep learning model. The features generated by MobileNetV2 are then classified using XGBoost into three classes, namely normal, benign, and malignant, with the model's performance evaluated using accuracy, precision, recall, and F1-score metrics. Through this approach, the study is expected to produce a more accurate and efficient breast cancer detection model to support medical personnel in clinical decision-making.

## 2. Methods

This study establishes a systematic framework so that the process of developing the Hybrid MobileNetV2 and XGBoost model can proceed in a directed manner, starting from the collection of mammography image data to obtaining breast cancer classification results, as shown in Figure 1.

The research workflow, as presented in Figure 1, begins with collecting mammography image data from RSUP Dr. M. Djamil Padang, after which the images undergo preprocessing involving resizing, normalization, and augmentation. The processed dataset is then split into training and testing data with an 80:20 ratio, before proceeding to the feature extraction stage using the MobileNetV2 architecture. The features extracted by MobileNetV2, in the form of a 1,280-dimensional feature vector, are then used as input for the classification stage using the XGBoost algorithm. The resulting model is then evaluated using accuracy, precision, recall, and F1-score metrics, before being used to predict mammography images into three classes, namely normal, benign, and malignant.

### 2.1 *Deep Learning*

This research employs a deep learning approach a subfield of artificial intelligence that uses multilayered artificial neural networks to automatically learn patterns from large-scale data. The ability of deep learning to recognize complex patterns in data such as images makes it highly relevant for medical image analysis, including breast cancer detection. In this study, deep learning is implemented through a Convolutional Neural Network (CNN) architecture, specifically MobileNetV2, which is used to automatically learn and extract feature representations of mammography images before they are classified using the XGBoost algorithm.

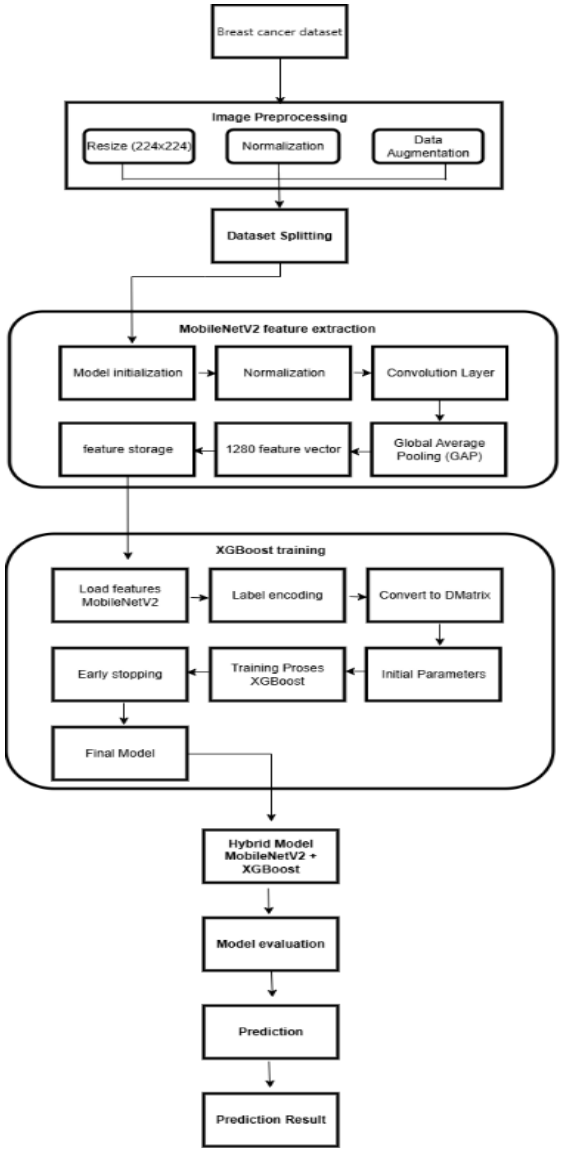



Figure 1. Research Framework

2.2. MobileNetV2

MobileNetV2 was selected as the feature extraction method because it is designed to overcome the limitations of conventional CNNs, which require substantial computational power, and has been proven to deliver high image classification performance with a lighter computational load, making it suitable for medical image analysis. This architecture applies depthwise separable convolution, which breaks down the convolution process into depthwise convolution and pointwise convolution to reduce the number of parameters and computational load without significantly reducing model performance. In this study, MobileNetV2 extracts important information from mammography images through convolution operations, the ReLU activation function, and Global Average Pooling (GAP), producing a 1,280-dimensional feature vector representing the important characteristics of breast cancer images.

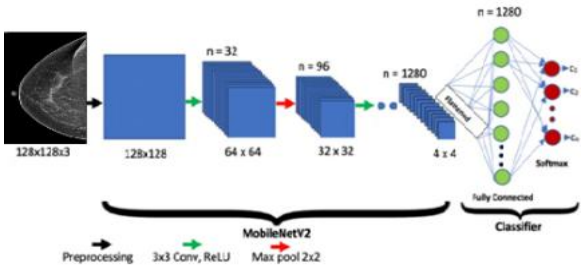



Figure 2. MobileNetV2 Architecture

Based on Figure 2, the MobileNetV2 architecture begins with the input of a mammography image that has undergone preprocessing, which is then processed using convolution layers, the ReLU activation function, and max pooling to progressively extract image features. The extracted features are passed to the feature map and summarized through Global Average Pooling (GAP) before entering the Fully Connected Layer, producing a 1,280-dimensional feature vector representing the important characteristics of breast cancer images to be forwarded to the classification stage using XGBoost.

2.3 XGBoost

The XGBoost algorithm was adopted for classification because of its effectiveness in handling complex data structures and improving accuracy. This algorithm works by building a model additively, combining a number of decision trees in stages to minimize the objective function using a second-order Taylor expansion approach. In this study, the feature vector resulting from MobileNetV2 extraction is converted into DMatrix format, then trained with hyperparameter settings and an early stopping mechanism to maintain model performance stability and prevent overfitting, before being used to classify images into the normal, benign, and malignant classes.

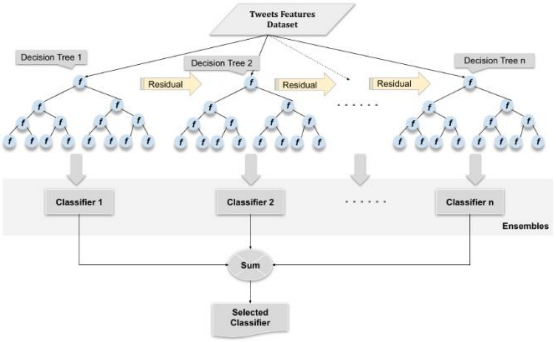



Figure 3. Architecture of eXtreme Gradient Boosting (XGBoost)

Figure 3 shows the architecture of the XGBoost algorithm, namely the sequential formation of a number of decision trees (Decision Tree 1, Decision Tree 2, up to Decision Tree n) from the same feature dataset. Each tree produces a classifier, and the next tree is built to

learn the residual (error difference) from the previous tree, so that each new tree corrects the prediction errors of the previous tree. All resulting classifiers are then combined through an ensemble mechanism, in which the prediction results of each classifier are summed to produce the selected classifier as the final model. In this study, this mechanism is applied to the feature vector resulting from MobileNetV2 extraction as the input dataset, allowing XGBoost to progressively improve breast cancer classification accuracy while keeping model complexity under control.

## 3. Results and Discussions

This chapter presents the implementation results and discussion of the proposed MobileNetV2–XGBoost hybrid model for breast cancer detection using mammography images. The discussion includes the dataset, preprocessing, feature extraction, model training, and classification performance evaluation.

### 3.1 Dataset

The dataset used in this study consists of mammography images obtained from RSUP Dr. M. Djamil Padang. The use of these data sources aims to increase the number of samples and the variation of image characteristics so that the developed model has better generalization ability. The dataset is grouped into three classes, namely Normal, Benign, and Malignant. The distribution of the dataset used in this study is shown in Table 1.

Table 1. Details of the Breast Cancer Mammography Image Dataset

| No | Data | Number | Format |
|---|---|---|---|
| 1 | Normal Breast Cancer | 66 | JPG |
| 2 | Benign Breast Cancer | 26 | JPG |
| 3 | Malignant Breast Cancer | 60 | JPG |

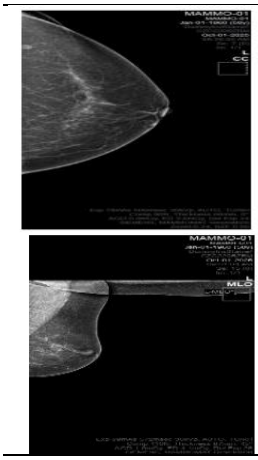
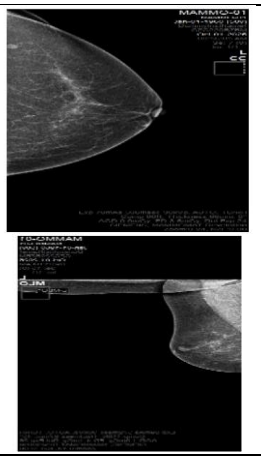
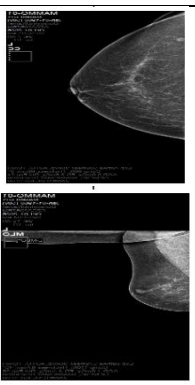
Based on Table 1, the research dataset consists of three categories of mammography images. The dataset is divided into three classes so that the model can effectively capture the distinctive characteristics of each class category during training, enabling it to perform multiclass classification more effectively. Following this, the complete dataset undergoes several preprocessing steps namely resizing, normalization, and augmentation prior to feature extraction via MobileNetV2 and subsequent classification using the XGBoost algorithm.

### 3.2 *Preprocessing*

The preprocessing stage is an initial process carried out to improve the quality of the image data before it is used in the feature extraction process using MobileNetV2. In this study, preprocessing consists of three main stages, namely resizing, normalization, and augmentation. The preprocessing stages applied are shown in Table 2.

Based on Table 2, the preprocessing process is carried out through three main stages. The resizing stage aims to standardize the size of all images to 224x224 pixels to match the input specifications of MobileNetV2. Next, normalization is performed using the preprocess_input function in MobileNetV2 to adjust the distribution of pixel intensity values so that the model learning process becomes more stable and efficient. Next, the data undergo augmentation through horizontal flip, rotation, and zoom operations, generating varied image representations while retaining the core characteristics of the breast tissue. This process lowers the likelihood of overfitting and strengthens the model's generalization performance.

Table 2. Results of Each Mammography Image Preprocessing Stage

| **Original Image** | **Resize (224x224)** |
|---|---|
|  |  |
| **Normalization** | **Augmentation** |
|  |  |

### 3.3 MobileNetV2 Feature Extraction

MobileNetV2 is used as a feature extractor to convert mammography images into numerical representations that can be used in the classification process. The MobileNetV2 model is initialized using pre-trained ImageNet weights, while the built-in classification layer is disabled (include_top=False) so that the model functions only to extract features. A Global Average Pooling (GAP) layer is then added to produce a more compact feature representation. The feature extraction

workflow using MobileNetV2 in this study is shown in Figure 4.

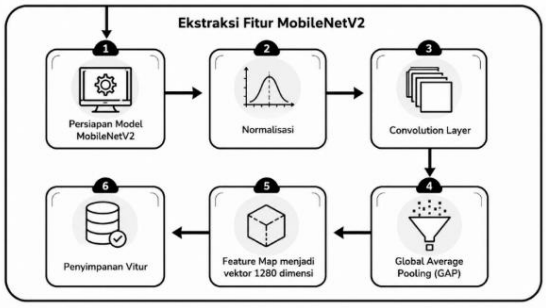



Figure 4. Feature Extraction Workflow Using MobileNetV2

Based on Figure 4, the mammography image that has undergone preprocessing with a size of 224x224x3 is processed using the MobileNetV2 architecture to produce a feature map representing the important characteristics of the image. The feature map is then summarized using Global Average Pooling (GAP) to obtain a 1,280-dimensional feature vector as a numerical representation of the mammography image, which is subsequently used as input data for the XGBoost algorithm. To further illustrate the feature extraction mechanism of MobileNetV2, the outputs of several filters in the initial convolutional layer were visualized. This visualization demonstrates how individual filters capture distinct characteristics of mammography images, such as edges, texture patterns, intensity variations, and anatomical breast tissue structures. The resulting feature maps are presented in Figure 5.

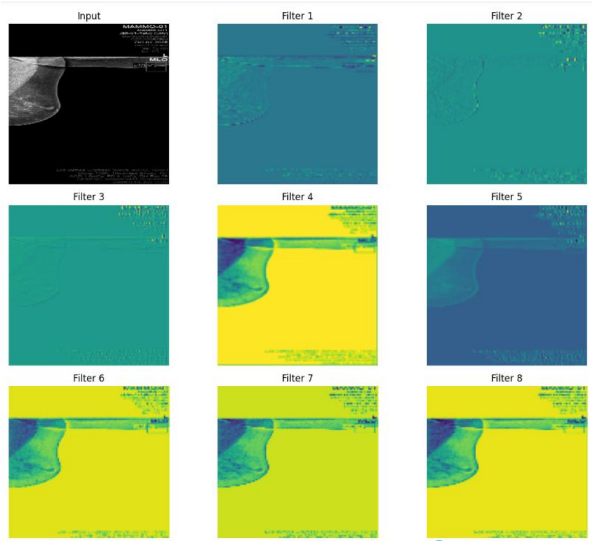



Figure 5. Visualization of Feature Maps from the Initial Convolutional Layer of MobileNetV2

Based on Figure 5, each filter generates a distinct activation pattern corresponding to the characteristics identified in the mammography image. Filters 1 to 3 primarily emphasize the contours and boundaries of breast tissue, whereas Filters 4 to 8 exhibit stronger responses to intensity distributions and texture patterns in specific regions. These differences in activation patterns indicate that each filter performs a unique role in extracting visual information from the mammography image. Through this process, MobileNetV2 learns increasingly discriminative feature representations that facilitate the differentiation of Normal, Benign, and Malignant mammography images. Subsequently, the extracted features are aggregated using Global Average Pooling (GAP) to produce a 1280-dimensional feature vector, which serves as the input for the XGBoost algorithm during the classification stage.

### 3.4 XGBoost Model Training

After the feature extraction process using MobileNetV2 is completed, the next stage is training the model using the XGBoost algorithm. The training process begins with loading the extracted feature dataset, followed by label encoding, converting the dataset into DMatrix format, determining initial parameters, the training process, and applying early stopping to obtain a model with optimal performance. The XGBoost model training stages are shown in Figure 6.

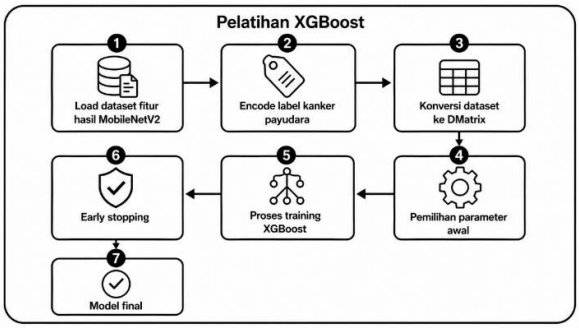



Figure 6. XGBoost Model Training Workflow

Based on Figure 6, the training process begins by loading the feature vector resulting from MobileNetV2 extraction as input data, followed by label encoding, conversion to DMatrix format, parameter determination, and training with early stopping to reduce the risk of overfitting. The trained XGBoost model is then used as the classifier in the hybrid MobileNetV2-XGBoost model to classify mammography images into the Normal, Benign, and Malignant classes. Following the completion of training, evaluation of the XGBoost model was conducted by examining the multiclass logarithmic loss (mlogloss) as well as the best iteration and best score obtained during the process. The implementation results of the XGBoost model training are presented in Figure 7.

Based on Figure 7, the training mlogloss decreased gradually, indicating that the model successfully learned the patterns from the feature vectors extracted by MobileNetV2. The best testing mlogloss of 0.64892

was achieved at the 61st best iteration. The trained model was subsequently saved as xgboost_mammografi.json and used for the mammography image classification stage.

```
↗IMPLEMENTASI PELATIHAN XGBOOST
============================================================
[0]     Training-mlogloss:0.96167       Testing-mlogloss:1.02389
[50]    Training-mlogloss:0.05492       Testing-mlogloss:0.66541
[71]    Training-mlogloss:0.03040       Testing-mlogloss:0.65071
============================================================
✅MODEL FINAL XGBOOST
============================================================
Best Iteration       : 61
Best Score           : 0.6489200749907826
Boosting Round       : 72
Status Model         : Berhasil dilatih
Status Penyimpanan   : Berhasil disimpan
Nama File Model      : xgboost_mammografi.json
============================================================
```

Figure 7. Implementation of XGBoost Model Training

3.5 *Evaluation*

The performance of the Hybrid MobileNetV2-XGBoost model was evaluated using test data (20% of the total dataset) that was not involved during the training process. The confusion matrix results are shown in Figure 8.

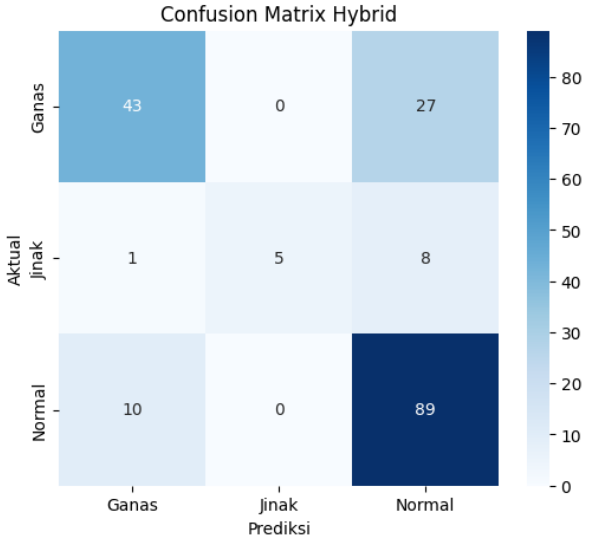



Figure 8. Confusion Matrix of the Hybrid MobileNetV2-XGBoost Model

Based on Figure 8, the model correctly classified 43 malignant data, 5 benign data, and 89 normal data. However, there were still misclassifications, namely 27 malignant data predicted as normal, 1 benign data predicted as malignant, 8 benign data predicted as normal, and 10 normal data predicted as malignant. These results indicate that the model has good classification ability, particularly for the normal class, while the benign class shows a relatively higher misclassification rate, likely due to the smaller amount of benign class data compared to the other classes. Details of the precision, recall, and F1-score values for each class are presented in Figure 8.

```
============================================================
CLASSIFICATION REPORT
============================================================
              precision    recall  f1-score   support

       Ganas       0.80      0.61      0.69        70
       Jinak       1.00      0.36      0.53        14
      Normal       0.72      0.90      0.80        99

    accuracy                           0.75       183
   macro avg       0.84      0.62      0.67       183
weighted avg       0.77      0.75      0.74       183
```

Figure 9. Classification Report of the Hybrid MobileNetV2-XGBoost Model

Based on Figure 9, the malignant class achieved a precision of 0.80, a recall of 0.61, and an F1-score of 0.69. The benign class had a precision of 1.00, a recall of 0.36, and an F1-score of 0.53. Meanwhile, the normal class achieved a precision of 0.72, a recall of 0.90, and an F1-score of 0.80. Overall, the model achieved an accuracy of 75%, with macro averages of 0.84 (precision), 0.62 (recall), and 0.67 (F1-score), while the weighted averages were 0.77 (precision), 0.75 (recall), and 0.74 (F1-score). The low recall value for the benign class (0.36) indicates that the model still frequently misclassifies benign images into other classes, making this class the main focus for performance improvement in future research, for example through increasing the amount of data or applying class balancing techniques. Overall, the evaluation results show that the Hybrid MobileNetV2-XGBoost model has a fairly good classification performance, particularly in recognizing the normal class, and has the potential to be used as a tool for early detection of breast cancer based on mammography images.

## 4. Conclusions

This study developed and evaluated a Hybrid MobileNetV2 and XGBoost model to detect and classify breast cancer based on mammography images sourced from RSUP Dr. M. Djamil Padang and the Kaggle platform. MobileNetV2 was used as a feature extractor that produced a 1,280-dimensional feature vector, which was then classified by XGBoost into the normal, benign, and malignant classes. The test results show that the model achieved an accuracy of 75%, a weighted precision of 77%, a weighted recall of 75%, and a weighted F1-score of 74%, with the best performance on the normal class. The benign class showed a relatively high misclassification rate due to visual similarity with other classes and a limited amount of data, making it the main focus for improvement in future research, for example through increasing the amount of data or applying class balancing techniques. Overall, the results of this study indicate that the hybrid MobileNetV2-XGBoost approach has the potential to be used as a tool for early detection of breast cancer based on digital images to support medical personnel in clinical decision-making, although additional data and class balancing are needed to more comprehensively improve the model's performance in the future.

## References


[1] *Who*.int, "WHO," who.int. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/breast-cancer

[2] Huljannah Mifta, Irawiraman Hadi, and Hasanah Nurul, "Frekuensi dan Karakteristik Kanker Payudara Pada Wanita Usia Muda di RSUD Abdul Wahab Sjahranie Samarinda tahun 2018-2020," *J. Kedokt. Mulawarman*, vol. 10, no. 1, pp. 1–11, 2023.

[3] Kemenkes.go.id, "kemenkes," kemenkes.go.id. [Online]. Available: https://kemkes.go.id/id/kanker-payudaya-paling-banyak-di-indonesia-kemenkes-targetkan-pemerataan-layanan-kesehatan

[4] R. E. N. Rongcai, W. U. Guoxiong, and C. A. I. Ming, "Analisis Struktur Covarians tentang Indeks Terkait Kesehatan pada Lansia yang Tinggal di Rumah dengan Berfokus pada Persepsi Kesehatan Subyektif," 2025.

[5] S. Azka and T. Arifin, "Perbandingan Arsitektur CNN Berbasis Transfer Learning untuk Klasifikasi pada BreastMNIST," vol. 02, pp. 192–200, 2025.

[6] R. R. Kothinti, "Deep learning in healthcare : Transforming disease diagnosis , personalized treatment , and clinical decision-making through AI-driven innovations," vol. 24, no. 02, pp. 2841–2856, 2024.

[7] A. Saber, T. Emara, S. Elbedwehy, and E. Hassan, "OPEN A novel approach for breast cancer detection using a Nesterov accelerated adam optimizer with an attention mechanism," pp. 1–14, 2025.

[8] G. A. Mahesa, A. E. Minarno, and Y. Azhar, "No Title," 2025.

[9] M. Faris, F. Rozi, and S. Mulyono, "Deteksi Kanker Kulit Melanoma Berbasis Android Menggunakan Convolutional Neural Network Arsitektur MobileNET v2," vol. 5, no. 2, 2023.

[10] S. Widodo and H. Brawijaya, "Hybrid sampling untuk meningkatkan akurasi deteksi kanker serviks pada data tidak seimbang : kajian komparatif," vol. 07, no. 2, 2025.

[11] M. R. Andryan, M. Fajri, and N. Sulistyowati, "Komparasi Kinerja Algoritma Xgboost Dan Algoritma Support Vector Machine (Svm) Untuk Diagnosis Penyakit Kanker Payudara," *JIKO (Jurnal Inform. dan Komputer)*, vol. 6, no. 1, p. 1, 2022, doi: 10.26798/jiko.v6i1.500.

[12] O. Shobayo, "Developments in Deep Learning Artificial Neural Network Techniques for Medical Image Analysis and Interpretation," pp. 1–31, 2025.

[13] G. D. Deepak and S. K. Bhat, "Computer Methods in Biomechanics and Biomedical Engineering : Imaging & Visualization Optimization of deep neural networks for multiclassification of dental X-rays using transfer learning," Comput. Methods Biomech. Biomed. Eng. Imaging Vis., vol. 12, no. 1, 2024, doi: 10.1080/21681163.2023.2272976.

[14] F. Twum, C. Carol, E. Ahiable, and S. O. Oppong, "Employing transfer learning for breast cancer detection using deep learning models," pp. 1–22, 2025, doi: 10.1371/journal.pdig.0000907.

[15] M. M. Labonno, D. M. Asadujjaman, M. Rahman, A. Tamim, M. J. Ferdous, and R. M. Mahi, "Early Detection and Classification of Breast Cancer Using Deep Learning Techniques," 2025

[16] Melya Susanti. (2022). Profil Kanker Payudara Di Rsup Dr M Djamil Padang Pada Tahun 2019. Nusantara Hasana Journal, 2(2), 101–108. https://nusantarahasanajournal.com/index.php/nhj/article/view/363/272

[17] Olawade, D. B., David-olawade, A. C., Wada, O. Z., Asaolu, A. J., Adereni, T., & Ling, J. (2024). Journal of Medicine , Surgery , and Public Health Artificial intelligence in healthcare delivery : Prospects and pitfalls. Journal of Medicine, Surgery, and Public Health, 3(January), 100108. https://doi.org/10.1016/j.glmedi.2024.100108

[18] Organization, W. H. (2024). Artificial Intelligence for Health. https://www.who.int/publications/m/item/artificial-intelligence-for-health

[19] P.Brody, C. T. and J. (2025). Pemanfaatan Kecerdasan Buatan sebagai Alat Bantu Diagnosis di Bidang Kesehatan : Literatur Review Utilization of Artificial Intelligence as a Diagnostic Aid in the Health Sector : A Literature Review. 9, 117–121.

[20] Pandia, M. (2024). Kajian Literatur Multimedia Retrieval : Machine Learning Untuk Pengenalan Wajah. Jurnal Ilmu Komputer Dan Sistem Informasi (JIKOMSI), 7(1), 161–166. https://doi.org/10.55338/jikomsi.v7i1.2758


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