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Classification Techniques in Finding Malignant Breast Cancer Detection

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Abstract

The most fundamental aspect of cancer is that it is marked by abnormal and uncontrolled cell growth, allowing it to spread to the surrounding areas of existing tissues. One of the most common cancers experienced by people in Indonesia, according to the Indonesian Ministry of Health, is breast cancer. The diagnosis of diseases, especially cancer, also requires a visual form that is later used as an image to determine the condition within the patient's organs. The use of mammography images is one implementation of X-rays aimed at revealing the structure of human bones and tissues. The use of images is also recognized in information technology in the field of digital image processing, which is useful for analyzing, enhancing, compressing, and reconstructing images using a collection of computational techniques. One application of digital image processing techniques for breast mammography images is recognizing the possibility of breast cancer through computer automation using classification methods supported by googlepredict.net architectures. The results obtained in this study use a dataset sourced from King Abdul Aziz University, totaling 2378 images. The method used in this research is Convolutional Neural Network (CNN), with the addition of the GoogleNet architecture. The convolution extraction method runs with the GoogleNet architecture, enhancing deep learning for optimal breast cancer recognition. The overall results of this study found an average precision value of 90%, recall of 92%, F-1 Score of 91.49%, and accuracy of 91.49%.

Keywords: Breast Cancer research, Classification, CNN, Convolutional Neural Network, Digital Image Processing, Image Analysis.

1. Introduction

Breast cancer originates from the glandular tissues, glandular ducts, and supporting tissues of the breast, rather than the surface. The presence of cancer cells in these areas is typically caused by genetic mutations or DNA damage to normal cells. Cancer manifests in numerous ways, however, breast, stomach, liver, colon, and lung cancer are the malignancies that result in the highest number of deaths. Women in Indonesia are disproportionately affected by breast cancer compared to other types of cancer. According to data from the Indonesian Ministry of Health, this particular ailment ranks among the leading causes of death in the country. According to the World Health Organization (WHO) in 2020, the number of cancer-related fatalities in Indonesia was reported to be 234,511 individuals (Sung et al., 2021; Yuliastuti et al., 2023). Breast cancer exhibits certain characteristics that can be discerned when it is present in an individual (Sung et al., 2021). An early indication is the presence of an anomalous mass in the vicinity of the breast. This mass typically has an uneven texture and is not associated with any discomfort.

High quality imaging instruments, including mammography, thermogram images, and MRI. The efficacy of a variety of screening techniques in the early detection of distinct breast cancer subtypes was evaluated in studies. Mammography is the most frequently employed procedure for the detection of breast cancer. The early detection of breast cancer is a difficult task, and mammography is not sensitive to dense breast tissue. This necessitates the implementation of supplementary methodologies, including ultrasound, to enhance the effectiveness of detection. The average measurement of a tumor detected by mammography is 1.66 cm.

The medical industry greatly profits from the implementation of this machine learning approach. which can identify drugs based on the outcome of a disease (Lestandy et al., 2021; Ma et al., 2019; Puttagunta & Subban, 2021; Syafa'ah et al., 2021; Syafa'ah & Lestandy, 2021). One study uses images and looks into categorization using the Convolutional Neural Network (CNN) technique. The accuracy of this research is between 20% and 50% (Putra et al., 2016). Subsequently, Rokhana et al. (2019) obtained research results with an accuracy of 95.3%, a sensitivity of 95%, and a specificity of 95% from one of his studies on the detection of bone contours and the identification of closed fractures using the CNN method on ultrasonic images (Rokhana et al., 2019). Because CNN is so good at recognizing both high- and low-resolution images, it is one technique that can be suggested for image detection (Dong et al., 2016; Sun et al., 2019).

Several studies have shown that CNN can have higher accuracy than image data. This means that while the neural network performs less well when classifying data, CNN can categorize new input that is present outside of the training data (Chauhan et al., 2018; Tobías et al., 2016). Therefore, the CNN method is used in this study to detect breast cancer. The CNN method is expected to be useful to find out cancer in the breast so that it can reduce the number of cases of such cancer.

CNN is one of the deep learning methods that extracts features from data. Additionally, CNNs have been applied to a number of computing tasks, such as image data classification and pattern identification. Generally speaking, CNN is used for image data identification and classification (Garga & Verma, 2020). Furthermore, according to (Shanthi & Sabeenian, 2019), CNN has a variety of topologies, including ResNet, LeNet, GoogleNet, AlexNet, and others. The CNN approach's architecture, known as GoogleNet, was unveiled in 2014. Among the numerous academics who have previously used the GoogleNet design is R. Anand, who employed it in his earlier work on CNN algorithms for face detection. When compared to 91.42% accurate classical machine learning techniques, Face study yields more accurate outcomes (Anand et al., 2020). Google has built a CNN architecture called GoogleNet, which is also referred to as Inception-v1. It stands out for using the inception module, which uses several convolutional layers with various filter sizes at the same time.

There are various benefits of classifying breast cancer using GoogleNet: 1) Multiscale Feature Search: GoogleNet can search for features at various scales thanks to the inception module. GoogleNet can extract significant features from radiological images of breast cancer by applying filters at different scales. The features of breast cancer can vary in size and complexity; 2) Efficient Parameter Usage: GoogleNet often uses more efficient parameters than other CNN architectures. This indicates that even though the design is rather intricate and deep, it typically requires fewer parameters to be trained than other architectures with comparable performance. This keeps overfitting at bay and permits using smaller datasets without sacrificing performance; and 3) Thus, by employing GoogleNet for breast cancer classification methods, one can achieve a blend of advantages in feature search, parameter efficiency, and excellent performance, even with little datasets.

2. Methods

This section describes the sequence of steps in the segmentation algorithm. There, the first procedure applies the method in a two-stage study. In the first step, pre-treatment is performed. In section 2.1, the pre-processing step converts the color image into a grayscale image to increase the image's clarity switches from 3D to 2D. The next step is to determine the region of interest (ROI) in the cancer area by cropping on the mammography image. The next step is to apply the Unsharp filter to the area defined by the ROI.

Previous research termed the dataset the Breast Imaging Data and Reporting System (BI-RADS), and used the mammography report formula to define the area that the ROI technique would target. The American College of Radiology (ACR) predicts tumor malignancy using a test material determination area with five labels for a single developing breast lump (American College of Radiology, 2014; Spak et al., 2017). A single breast lump that develops.

Cancer is defined by the size of the growing node according to size or stage regulation: Stage 0 is ductal carcinoma in situ (DCIS), which encompasses stages I (1) through IV (4). The first stage is stage I. According to the TNM classification system used by the American Joint Committee on Cancer (AJCC), the extent of cancer metastasis is inversely proportional to the numerical value (Kalli et al., 2018).

The next step, feature extraction and classification in Section 2.2, describes segmental image processing in breast cancer research, which is considered very suitable because the CNN method gives good results in implementing image processing algorithms. The utilization of CNN in breast cancer research provides a significant advantage in analyzing medical images. CNN is specifically designed to recognize patterns and complex features in images, including mammography. Its main advantage lies in its ability to automatically extract features, eliminating the need for time-consuming manual preprocessing. In the context of breast cancer research, where the identification of specific characteristics is crucial, CNN can comprehend the context and hierarchy of relationships between image features.

In addition, CNN exhibits responsiveness to changes in image scale, hence maintaining its capacity to identify cancer entities across different magnifications. sizes and severity levels. Compared to other machine learning strategies like SVM, machine learning has been shown to be more effective at classifying data. The Multi-Layer Perceptron (MLP) was developed similarly to CNN, specifically for 2D images, as shown in Fig. 1.

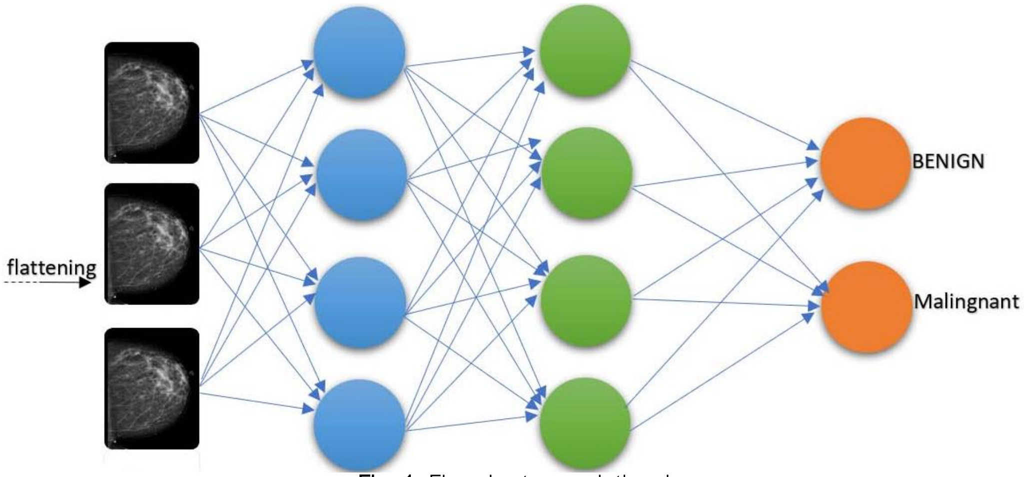

Fig. 1. Flowchart convolutional.

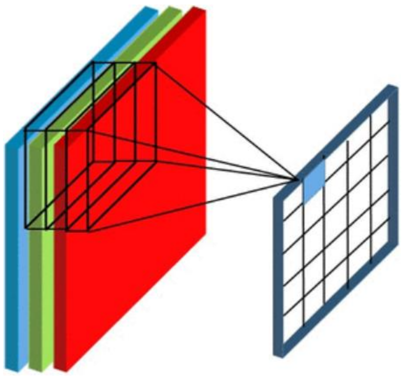

Fig. 2. CNN convolution process.

Fig. 1 depicts a diagram where each node is linked to the nodes that come before and after it. Then, in the output layer, there are multiple classes (categories). For example, the topmost image has two classes, indicating whether it belongs to the Benign or Malignant category. If there are more than two classes, like five categories, then the output layer contains five nodes. The result of the 2 categories in the image above (whether the image is clear or malignant) is a probability. It will output the probability value for each category. If it guesses that the image is malignant, the final probability values could be: clear = 0.2, malignant = 0.87. CNN method it will be forward propagation and backpropagation. The most instrumental in determining whether the input image falls into categories A, B, and so on is the weight that each node has. This weight will always be adjusted every epoch. Because of the nature of the convolutional process, only 2D CNNs, such as image and speech recognition, are applicable.

The architecture of this method is 2, namely feature extraction and classification. The CNN procedure consists of two layers, the conventional layer and the unifying layer (Kamencay et al., 2017). The learning phase uses backpropagation, and the classification phase employs the CNN extraction method along with the Google Predict net function (Tobías et al., 2016). Using the CNN method shown in Fig. 2 with image extraction, it is possible to separate the object with the resulting color for research classification with the color vector of the taught pixels to generate the desired nodal area.

2.1. Pre-Processing

Prior to algorithmic data processing, this step involves conducting breast cancer mammography dataset analysis and subsequently performing Region of Interest (ROI) segmentation. ROI segmentation refers to the process of calculating the return on investment (ROI) of an input frame. ROI segmentation entails the process of choosing a certain region within the frame, ascertaining the proportions of the rectangle approach, and creating a rectangular ROI within the frame. Next, utilize the strained blunted object prior to the process of extraction, as depicted in Fig. 3.

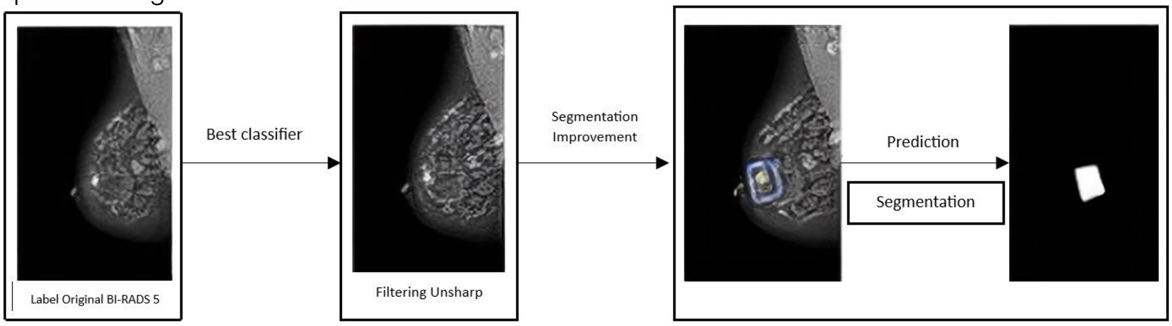

Fig. 3. Flow pre-processing.

In order to use the CNN method, 3D image data, specifically mammography images from King Abdul Aziz University's Kaggle, must first be processed in order to convert them into 2D image data. This process demonstrates precisely how the BI-RADS 5 image labels are processed, beginning with image acquisition from dataset B5. To sharpen the distinction between the tissues in the breast area, pixels are filtered using a blur filter prior to the ROI step, thereby highlighting the parts that can be anticipated as breast cancer locations. There are nodes around the chest image, which correspond to the predicted stage of malignancy according to the notation. In the third process, start entering the ROI stage, which is part of the initial segmentation of the given nodal region. If you have a potential breast cancerous area segment, the selected area is formed by dividing it into binary black and white. The process formed due to ROI is shown in the last process in Fig. 3.

2.2. Feature extraction and classification

2.2.1. Convolutional Layer

At the output of the layer before the convolution layer, the convolution operation takes place. The CNN procedure's primary step is this shift alternation. Convolution is a mathematical term that refers to repeatedly applying one function to another function's output. Convolution in image processing refers to the addition of a kernel (yellow box) to an image with all potential variations, as seen in Fig. 4. A common green box colors a blended image. The kernel moves from the top left corner to the bottom right corner. So, the result of image convolution can be seen in the correct image.

Image data is convolved to extract features from the input image. Depending on the spatial information in the input data, convolution produces a linear transformation of the data. Which convolution kernel is employed is determined by the weights of this layer, allowing the convolution kernel to be trained using the data from CNN.

CNN also knows the process of pacing and filter replacement. The filter moves to the right of the image edge and then changes to move down one edge, while zero padding means adding one edge to the image. Adding 1 to the complete means adding 0 to each edge of the image. Some different types of filters, stages, and null pads in the convolutional layer are (Dumoulin & Visin, 2018):

a) Zero Padding, Unite stride.
If the convolution plane has zero padding and step length, it means 0 is added to each pixel on all sides of the image and the filter is shifted 1 step. You can use Eq. (1) to determine the dimensions of the resulting feature, where p is the amount of padding (Fattah, 2021).

$$\boldsymbol{h = (i - r) + 2p + 1} \quad (1)$$

b) Zero Padding, no unit stride in determining the dimensions of the resulting feature with padding and no unit stride use Eq. (2).

$$\boldsymbol{h = \left[\frac{i + 2p - r}{s}\right] + 1} \quad (2)$$

From the above formulation comes a type of method where the filter is created in one step and without solving. Therefore, the point function uses the following Eq. (3).

$$C_{h,h} = f(\sum_{x=1}^{r} a_x \times w_x + b) \tag{3}$$

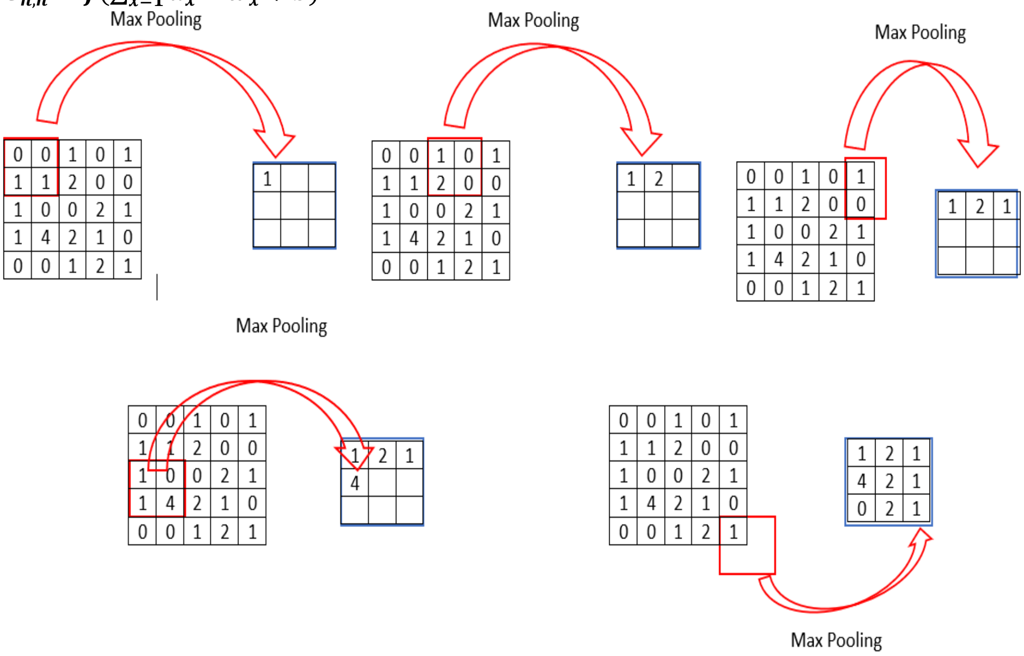

Fig. 4. Convolution operation.

The convolution stage is shown in Fig. 4, where a new layer is created during the pooling stage. Next, select two by two pixels on the left side of the image, which is the feature map's rightmost point. It is not always necessary for a $\mathbf{2} \times \mathbf{2}$ to be $\mathbf{2} \times \mathbf{2}$; $\mathbf{3} \times \mathbf{3}$, $\mathbf{4} \times \mathbf{4}$, or even $\mathbf{5} \times \mathbf{5}$ might be used instead. However, $\mathbf{2} \times \mathbf{2}$ is what is frequently used in the literature. These $\mathbf{2} \times \mathbf{2}$ pixels contain four numbers: 0; 1; 0; and 1. It only takes the maximum value during the operation, which is why it's called max pooling. Remove the other three numbers before inserting the number 1. To ensure that the data that has been searched for the maximum value does not contain redundant data (not examined for the nth time), two columns have been shifted to the right in the following image. The image contains the following four values: 1, 0, 2, and 0. Moving two additional columns to the right, here's an example. With two values now set to 1 and 0, it makes no difference that it is outside the feature map's bounds after shifting two columns to the right. One represents the greatest value. From here, descend two rows and keep going until it reaches the finish line. Its ability to identify the most important quality ratings is what gives max pooling its usefulness. What stands out the most is how highly adjustable but maximally repeatable the pixel values are.

When identifying a cancerous image, for instance, the basic malicious characteristic persists and is kept regardless of the image composition (tilted, various colors, reduced). This is because the major malignant feature (maximum value) may be detected.

a) No Zero Padding, Unit stride

A shift (step) is present when there is no zero padding and a unit step. The dimensions of the features obtained from the convolutional layer shown in Eq. (4) depend on the dimensions of the input matrix and the dimensions of the filter matrix.

$$\boldsymbol{h} = (\boldsymbol{i} - \boldsymbol{r}) + \mathbf{1} \tag{4}$$

Where: Convolutional layer feature dimensions are h, i, and r, where r is the dimension of the filter matrix $(\boldsymbol{n} \times \boldsymbol{n})$, and n is the dimension of the input matrix.

b) No Zero Padding, no Unit stride

No unit stride means the movement (stride) is more than 1. In determining the dimensions of the resulting feature without zero padding and no unit stride, namely in Eq. (5).

$$\boldsymbol{h} = \left[\frac{\boldsymbol{i}-\boldsymbol{r}}{\boldsymbol{s}}\right] + \mathbf{1} \tag{5}$$

2.2.2. Pooling Layer

Additional steps occur when extracting features from a CNN. That is called pooling or commonly called subsampling. In this layer, matrix reduction or miniaturization occurs. The pooling layer is further divided into two processes: maximum and intermediate or mesonominal (Zufar, 2016). The calculation for each pooling layer filter uses maximum pooling which is calculated in Fig. 5.

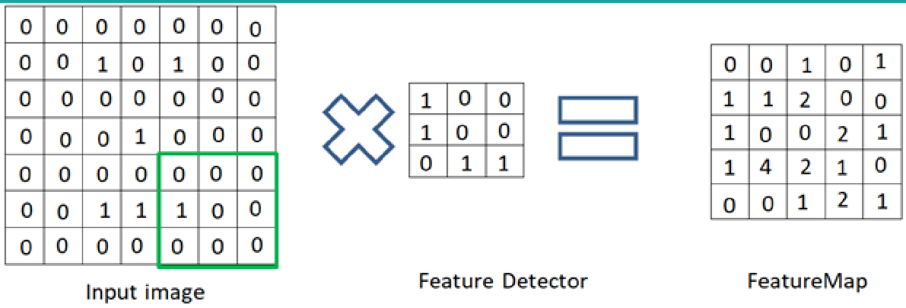

Fig. 5. Pooling Layer (Kamencay et al., 2017).

In Fig. 5, the input image with pixels having a size of $\mathbf{7} \times \mathbf{7}$ is reduced to a smaller size of $\mathbf{5} \times \mathbf{5}$. This is indeed one of the main purposes of the feature detector. Through the feature detector, the image processing process becomes faster because the processed pixel data is also getting smaller (less).

2.2.3. Flatten or Reshape

Flattening or reforming is a procedure in which the resulting matrix is changed from a layer that is connected to a substrate. $\boldsymbol{n\,X}$ splicing layer to $\boldsymbol{n} \times \mathbf{1}$ matrix form. Fig. 6 illustrates how the smoothing process' output is fed into the subsequent classification step (Sena, 2017).

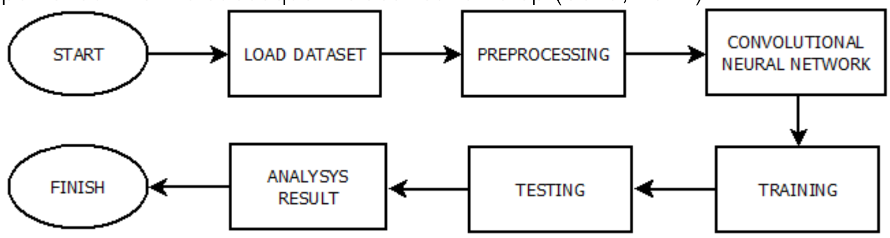

Fig. 6. Flowchart system.

In this study, CNN's classification procedure was carried out using the GoogleNet architecture. This architecture is well suited to the methods used in this investigation, which include a low error rate of roughly 6.70%. The percentage came from the winner of the ILSVRC competition, which also marked the first use of GoogleNet (Krishna & Kalluri, 2019).

Every year between 1998 and 2015, a variety of architectures have been used to enable deep learning skills for the production of image processing capabilities. In this study, the GoogleNet model has been used to segment the breast cancer region before classification, allowing the Convolution approach to be employed for breast cancer area identification. Architectural models can typically improve the accuracy of the method used. Thus, a high degree of precision is deemed unsuitable for processing, as evidenced by the accuracy level effectiveness results published at the ILSVRC competition. LeNet has a relatively high mistake rate of 28.2% for the average error rate of the oldest design in 1998, with a parameter number of 600,000 usages. Eventually, in 2012, AlexNet released a new design with an average error rate of 16.4% for using 62.3 million test materials, which was lower than previous iterations. Subsequently, the VGG architecture was developed with an average error of 7.30%, utilizing 138 million research from 2014. As one of the few studies on the use of the architecture, GoogleNet, which was released by Google Incorporation the same year as VGG, has an average inaccuracy of 6.70% and was only published 4 million times. The most recent design, Resnet, was released a year after GoogleNet first appeared. It has a very high degree of accuracy, with an average error of only 3.57% when the architecture is used for 25 million studies.

According to the results of published research, each architecture has strengths that can be used to formulate deep learning accuracy using a variety of methods. Some of the most recent architectures are particularly adept at avoiding failure when analyzing image data. The GoogleNet architecture has quite a lot of layers, from 5 to 22 layers, but with so many layers, the accuracy of the analysis is high. The way GoogleNet works is based on activation values in the deep network that are not fully relevant due to previous correlations because it requires activation values that are not fully connected (Bi et al., 2019). Under these circumstances, GoogleNet has an initial module layer inspired by the human visual cortex model, which plays a role in optimizing the sparse structure to support computation. In the GoogleNet architecture, in the initial module layer, $\mathbf{1} \times \mathbf{1}$ matrix convolution is performed before $\mathbf{3} \times \mathbf{3}$ and $\mathbf{5} \times \mathbf{5}$ matrix convolution to reduce the module dimension, which is essential to increase the depth of analysis and expand the network without reducing the system speed. The strength of GoogleNet lies in the inception module. The output module consists of several small convolutions used for reduction, shown in Fig. 7.

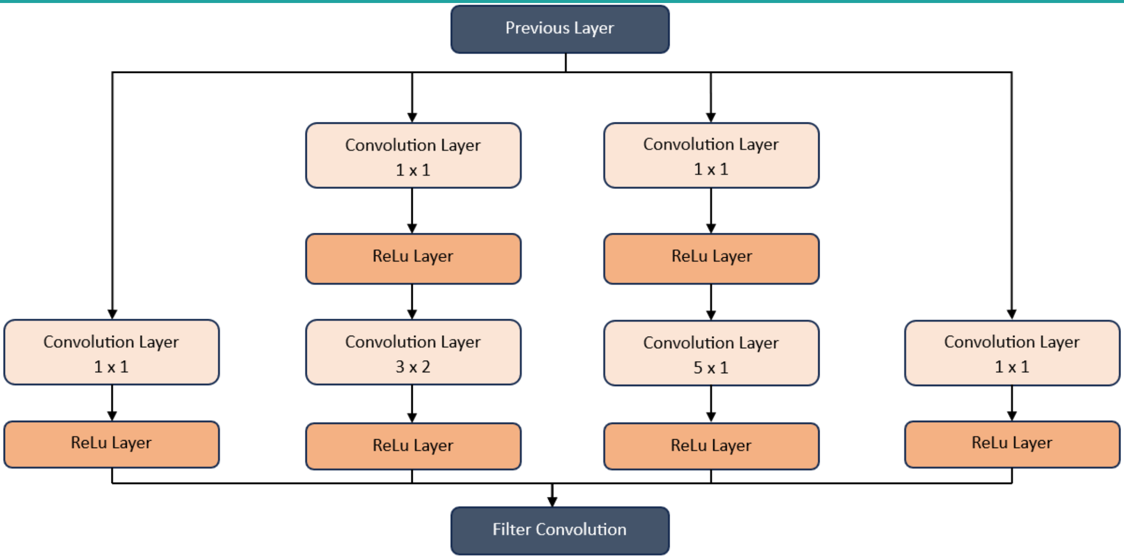

Fig. 7. GoogleNet Inception Modules (Faizin et al., 2022).

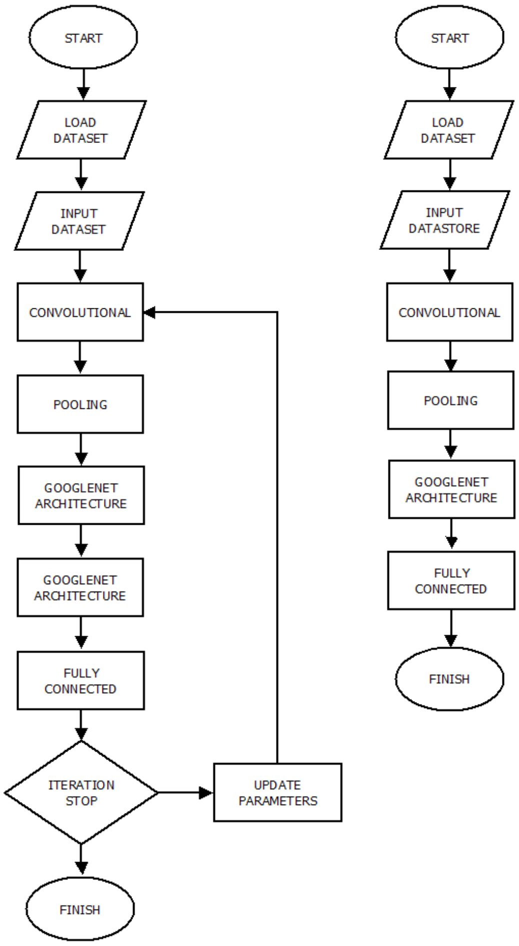

Fig. 8. Training process and testing process.

This architecture was used to improve the network yield by identifying the originating network in the breast cancer node region more clearly. The approach was processed starting with a sampling of the A and B records corresponding to BI-RADS labels 1 through 5, based on the tested labels, in order to obtain the segmented images. Then, the 2000 dataset had all labels from 0.2% of the test data and 0.8% of the training data. Once the prediction procedure has been completed, the algorithm shows the outcome of the GoogleNet architecture-based secret image extraction procedure. It produces the probability result based on whether the input label satisfies the required accuracy or not. The obtained accuracy is around 91.49%, and 90% sample repeatability is used in the test result acquisition process. Additionally, the network depicted in Fig. 8 was examined in this study to determine whether the probability labels that are currently in place are appropriate.

The training and testing program flow for executing the extraction procedure of the CNN method with GoogleNet architecture necessitates iterative processing initially to get superior classification. GoogleNet is an architectural model that initially gained recognition by winning first place in the ILSVRC competition. It has since been acknowledged as a highly effective deep learning model for digital image processing.

3. Results and Discussion

This study makes use of a collection of mammography images with five labels representing breast cancer based on BI-RADS classifications that were sourced from kaggle.com. There is evidence to suggest that breast cancer grades can be predicted from I to V. Systematic machine learning for digital imaging starts with pre-processing. Furthermore, segmenting regions that may include excess tissue structure that results in nodes or lumps in an individual's breast tissue is made easier with the aid of the ROI method. The King Abdul Aziz University mammography Dataset, which contains 2380 registered mammography images, is the source of the MIAS (Mammographic Image Analysis Society) dataset used in this investigation. Based on BI-RADS, this dataset is categorized into 1–5 groups. While 1865 is present in the class in BI-RADS 1, the source does not give a class in BI-RADS 2. The distinction of classes is maintained in BI-RADS 3, which contains 387 mammography images; BI-RADS 4, which includes 102 images; and BI-RADS 5, which has 24 images, the highest class in breast cancer.

An image or picture can be defined as $f(x, y)$, which is two-dimensional and symbolizes the x and y coordinates as a function that has elements of a point composed of gray colors ranging between black and white depending on the energy level recorded, each image consists of a set of pixels that are useful so that machines can easily understand the image. Pixels are also called digital numbers, and each block illustrated is worth 1 pixel. In its use, the mammogram image in this dataset consists of 2816×3584 pixels, which start from three dimensions and then are converted into two dimensions so that they can be processed by Mathlab software using the CNN algorithm because image data processing in the convolution method can only be done in two dimensions. Next, pre-processing is done with the image to be executed so that the mammogram image shows differentiation between colors to sharpen the image using the Unsharp filter. The segmentation stage is still included in the scope of pre-processing by performing manual object discrimination using the ROI (Region of Interest segmentation) method. For this reason, pre-processing will run according to the corridor with the technique to be extracted.

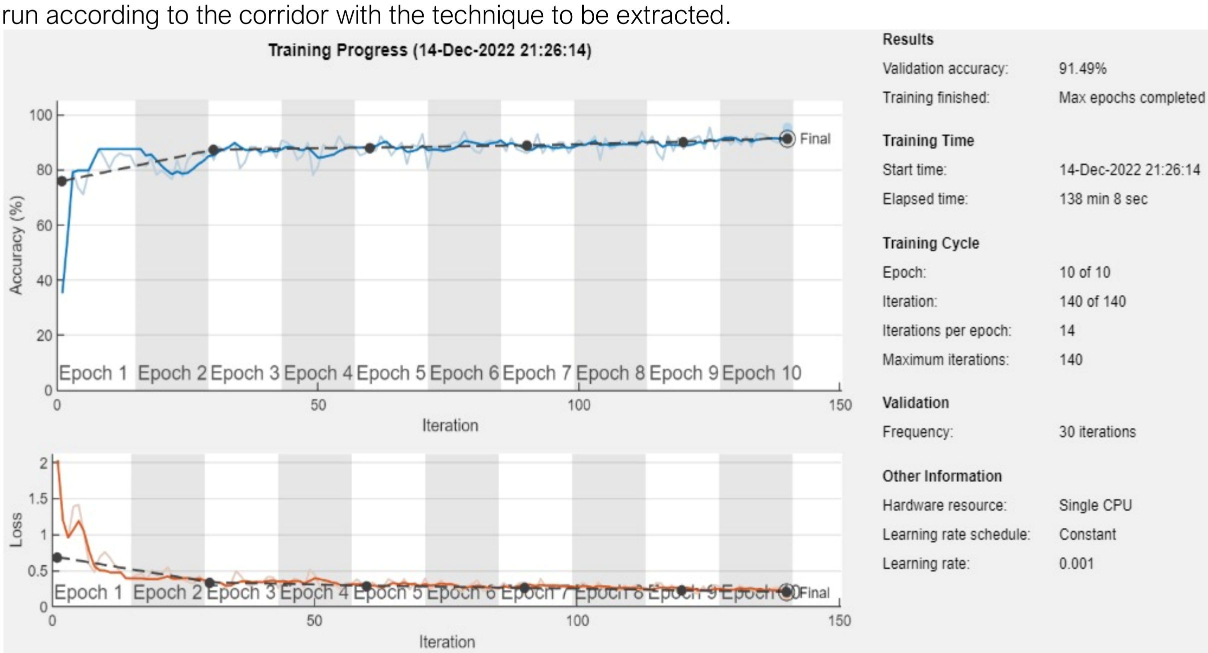

Fig. 9. Graph result training process and validation process.

After the image has been segmented by selecting certain regions for additional CNN processing, the extraction procedure starts. With GoogleNet architecture, the test results in this study are excellent, with 0.8 for training data and 0.2 for test data. The accuracy rate of the results is 91.49%. Recall or retesting results at regular intervals yield a percentage of almost 90%. It has been demonstrated that the study done for the 2019 ILSVRC competition produces the best results in digital imaging. Fig. 9 displays the research's findings.

The segmentation of the image into distinct parts for subsequent processing using the CNN method initiates the extraction process. The study's test results, which combine the GoogleNet architecture with 0.8 test data for training and 0.2 test data for testing, are excellent and yield an accuracy rate of 91.49%. Recall or retesting results at regular intervals yield a percentage of almost 90%. It has been demonstrated that the study done for the 2019 ILSVRC competition produces the best results in digital imaging. Fig. 9 displays the outcomes of the extraction procedure.

The pre-processing results are so good that several convolution test results are obtained. In order to explain these findings, the accuracy results of recall, F1-Score, and precision were acquired in this investigation. Table 1 shows the results of this research.

Table 1.
Average result BI-RADS category based on accuracy, recall, and F-1 Score

Class	Precision	Recall	F-1 Score	Total Data
BI-RADS 1	0.91	0.95	0.93	1,856
BI-RADS 3	0.89	0.90	0.89	387
BI-RADS 4	0.90	0.92	0.91	102
BI-RADS 5	0.91	0.94	0.94	24
Average	0.90	0.92	0.91	2,378

In machine learning, metrics assess the model's performance. In this study, recall evaluates the model's ability to capture all real positive outcomes, while precision analyzes the model's accuracy in recognizing breast cancer patients. Both are essential for assessing GoogleNet CNNs' accuracy in identifying breast cancer in Indonesian women. The dataset retrieved for the Mammogram Image category does not exist from the obtained source, as can be seen from the table, which indicates that there is no BI-RADS 2 label. It can be seen that the BI-RADS label, indicating the prediction of cancer malignancy, is more accurate than the BI-RADS 5 label due to the image indicator clearly showing abnormal tissue. In terms of the tested data, which amounted to only 24 with repetition, it resulted in a validation accuracy of 91.49%. Additionally, the average F1-Score value, calculated from the quotient of precision with a recall of 94%, further underscores the reliability of the CNN GoogleNet method. This research is deemed suitable for aiding health workers, especially internal medicine specialists, in diagnosing breast cancer from the initial symptoms to analyzing the severity of malignancy, which affects almost half of the female population in Indonesia.

4. Conclusions

One of the conclusions that can be drawn from this research is that there are a lot of additional sources of information outside of MIAS when it comes to the collection of mammography data. The Kaggle dataset, which was obtained from King Abdul Aziz University, contains approximately 2,378 mammography images. This is because, during the extraction process, CNN's method produces very long-lasting results and requires a large amount of laptop memory. The methodology used in this study is manual ROI utilization. The study identifies network areas where abnormal network nodes are present in a large number of datasets. King Abdul Aziz University's Breast Cancer Mammogram Dataset, which can be found on the kaggle.com website, was one of the datasets used in this research.

When compared to the GoogleNet architecture, the results of the convolution method extraction are highly appropriate. The classification process carried out improves the accuracy of deep learning for image data in identifying breast cancer, potentially assisting medical professionals in treating patients from the time their symptoms first appear until their cancer is diagnosed. After processing the recall details of the successful test at the same number, which is around 92%, the extraction of the research results obtained a total accuracy of 90%. The average of the category results tested on the f-1 Score is more than 91%. Future research recommendations: if utilizing the CNN approach, which takes a while to complete, you should use a tool that can handle a sizable amount of data. Additionally, the CNN method with GoogleNet architecture can process a variety of other case studies and excellent image data that can be re-evaluated using different methods and architectures to ascertain the efficacy of machine learning algorithms.

5. CRediT Authorship Contribution Statement

Adithya Kusuma Whardana: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Supervision, validation, and Visualization. **Abdul Latief Mufti:** Conceptualization, Methodology, Resources, Software, Writing – original draft, and Writing – review & editing. **Hendar**

Hermawan: Conceptualization, Methodology, Resources, Software, Writing – original draft, and Writing – review & editing. **Umar Alfaruq Abdul Aziz:** Conceptualization, Methodology, Resources, Software, Writing – original draft, and Writing – review & editing.

6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7. Data Availability

This study uses the King Abdul Aziz University breast cancer mammography dataset, which is available on the Kaggle website.

8. References

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