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A COMPARE: BREAST CANCER PREDICTION USING DEEP LEARNING

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ABSTRACT— Breast cancer sees millions of new cases recorded each year, with thousands succumbing to the disease. Early detection can prevent and effectively treat cancer, extending lives. Building deep learning models for breast cancer detection has shown significant progress and applications in the medical field. This study utilizes various deep learning models, from basic to advanced, to compare their performance. Models such as Convolutional Neural Networks (CNNs), CNN variants, and Transformer models are employed. CNN achieves an accuracy of 88% on validation set, while MobileNet reaches 85% and the Transformer model achieves 94% and the best model is EfficientNet reaches 93 %. Activation functions ReLU and optimization functions Sigmoid are utilized.

Keywords— Breast Cancer, deep learning, classification, Transformer, MobileNet, CNN.

I. INTRODUCTION

Breast cancer primarily affects women, with an estimated 1 in every 8 cancer cases being related to breast cancer, making it a prevalent form of cancer. According to the World Health Organization (WHO), in 2020, there were approximately 2.26 million new cases of breast cancer globally, resulting in about 658 thousand deaths. In Vietnam, there were around 21 thousand new cases and approximately 9 thousand deaths [1]. Early detection and timely treatment can significantly prolong life expectancy. According to experts, the five-year relative survival rate for breast cancer is 90%. This means that out of every 100 women diagnosed with breast cancer, 90 are expected to survive for five years following diagnosis. The ten-year survival rate for breast cancer is 84%, indicating that 84 out of 100 women diagnosed with breast cancer are expected to survive for ten years. The fifteen-year survival rate for invasive breast cancer is 80% [2]. Early detection is crucial for effective treatment and patient survival. Today, numerous studies focus on developing machine learning and deep learning models for breast cancer detection and diagnosis in the medical field. These models learn from data and make predictions, showing promising results and highlighting the potential of Artificial Intelligence (AI) to assist in disease detection and treatment, reducing errors in diagnosis and treatment processes.

II. RELATED WORK

Breast cancer remains a significant global health issue, with millions of new cases diagnosed annually. Early detection is vital for effective treatment and improved patient outcomes. Recent advancements in artificial intelligence (AI) and machine learning have shown promise in enhancing breast cancer detection and diagnosis. This report aims to review current research in this field, focusing on related works that utilize deep learning, machine learning, and multi-modal imaging techniques. By examining these studies, we can better understand the current landscape of breast cancer research and the potential of AI in improving healthcare outcomes.

Wang et al. proposed a deep learning approach utilizing convolutional neural networks (CNNs) for computer-aided diagnosis of breast cancer. Their method demonstrated promising results in detecting and classifying cancerous regions in mammograms, paving the way for automated diagnostic systems [3].

Cruz-Roa et al. proposed a deep learning framework based on CNNs for automated classification of breast cancer histopathological images. Their method showed high accuracy, demonstrating the potential of deep learning in computer-aided diagnosis [4].

Arevalo et al. utilized CNNs for predicting breast cancer in digital mammograms, achieving notable accuracy and sensitivity. Their work contributes to early diagnosis and treatment strategies for breast cancer [5].

Janowczyk et al. introduced a deep learning-based method for automated detection and classification of breast cancer in whole slide images. Their approach demonstrates the potential for efficient and accurate diagnosis [6].

Wang et al. proposed a fusion approach of multiple deep CNN models for breast cancer diagnosis, achieving enhanced performance compared to individual networks. Their work underscores the effectiveness of ensemble methods [7].

Spanhol et al. introduced a deep learning approach enhanced with genetic algorithm optimization for breast cancer histopathological image classification, demonstrating improved accuracy and robustness [8].

Agarwal et al. investigated the application of deep learning techniques for the classification of breast lesions in MRI images, demonstrating promising results and potential for enhancing diagnostic accuracy [9].

Liu et al. presented a hybrid approach combining deep learning-based features with a random forest model for breast cancer diagnosis and prediction. Their method achieved high accuracy and interpretability [10].

Kallenberg et al. provided a comprehensive review of deep learning approaches for breast cancer detection and diagnosis from mammograms. The review highlights advancements, challenges, and future directions in the field [11].

Li et al. conducted a comprehensive review of deep learning methods for improving breast cancer diagnosis, covering various aspects such as image analysis, feature extraction, and classification techniques [12].

III. METHODOLOGY

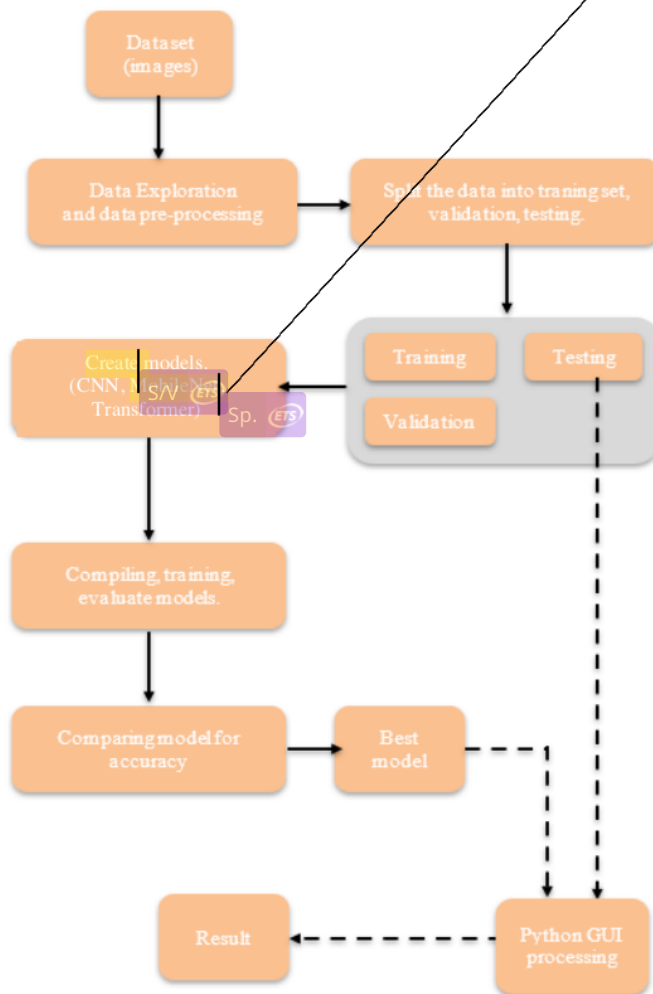


Fig 1. Proposed method diagram

In this project, we propose a method employing deep learning, specifically convolutional neural networks (CNNs) and their variants, advanced deep learning architectures such as MobileNet, Transformer. This study suggests utilizing these models for detecting cancer on a histopathological image dataset. Fig 1 depicts the proposed model step-by-step, from data collection to model training for breast cancer detection. After data collection, data exploration and preprocessing are necessary before diving into the training model. Then, the dataset is split into training, validation, and test sets. The training and validation data are used to train the models. After training, the models are compared and evaluated for performance to select the most accurate one. Next, the testing data are used in the graphical user interface program for testing and result analysis, leading to the final outcomes.

IV. DATASET

Firstly, data collection is initiated. This study utilizes the publicly available Kaggle dataset of invasive ductal carcinoma (IDC) histopathological images of breast tissue [13]. The initial dataset comprises 162 whole slide images of breast cancer (BCa) specimens scanned at 40x magnification. From these, 277,524 patches of size 50 x 50 were extracted (198,738 IDC negative and 78,786 IDC positive). Each patch file is named in the format: u_xX_yY_classC.png. For instance,

10253_idx5_x1351_y1101_class0.png, where u denotes the patient ID (e.g., 10253_idx5), X represents the x-coordinate of the location from which this patch was cropped, Y represents the y-coordinate of the location from which this patch was cropped, and C denotes the class where 0 indicates non-IDC and 1 indicates IDC.

For negative label data, typically, the color tends to be pink compared to positive labels, which are usually darker in color, indicating stronger cell development—a common observation in cancer cases. Fig 2 provides examples of negative images, while Fig 3 illustrates examples of positive images.

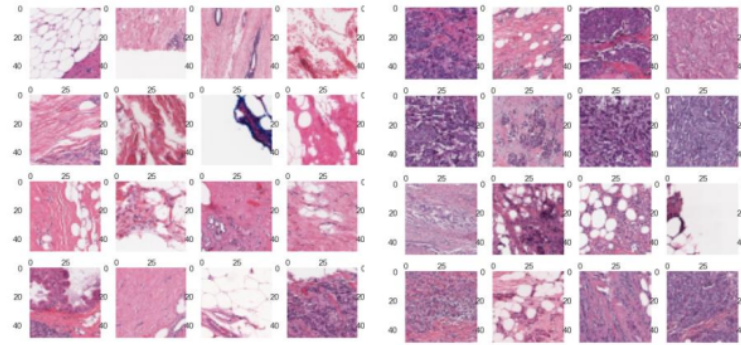


Fig 2. No breast cancer – IDC (-)

Fig 3. Breast cancer – IDC (+)

Cancer cells often cluster together, which can be visualized through binary labels in Fig 4. Each image represents the entire slice of the patient, which is then segmented into 50*50-sized patches like those shown in Fig 2 and Fig 3.

The data will be normalized to scale, aiming to enhance performance and improve learning capabilities. However, for the Transformer model, scaling normalization is not necessary due to the model's input features' ability to learn data characteristics without requiring proportional normalization.

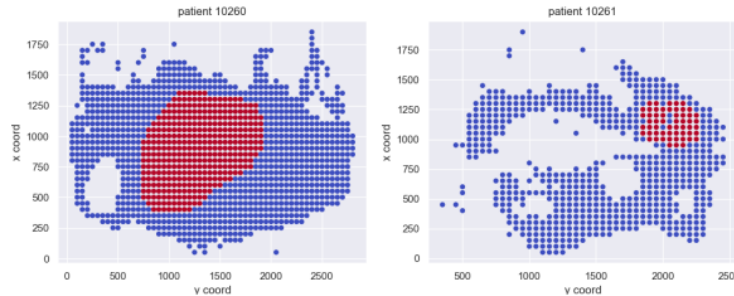


Fig 4. Coordinate image of the entire slice

Fig 5 displays the entire slice of the original image on the left side and, on the right side, points marked in red corresponding to the areas containing cancer on the left side.

Next, the data will be divided into training, validation, and testing sets. Due to hardware configuration limitations, only 100,000 images will be used for training, comprising 50,000 images from negative labels and 50,000 images from positive labels. Among these, 20% of the total training data will be allocated for model validation during the training process. The remaining data not used for training will be utilized for model testing after training is completed.

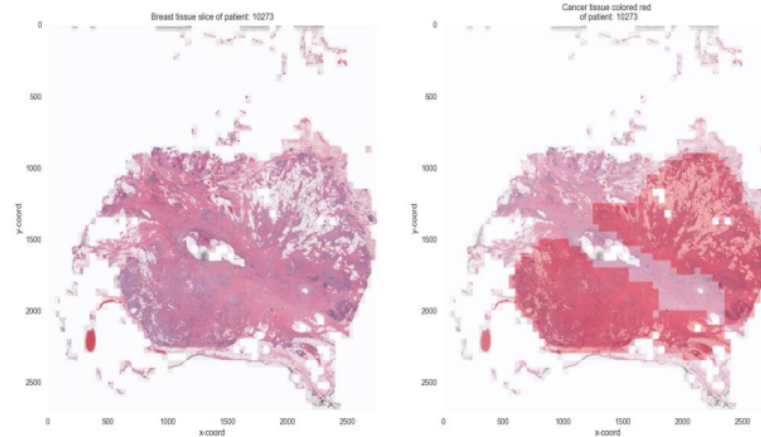


Fig 5. Total images on slice

V. IMPLEMENTATION

To implement this project, various methods are proposed, but in this study, five suggested models will be utilized. In reality, there are numerous methods to choose from and deploy, with each method yielding different results. Depending on the intended purpose, appropriate choices can be made. After thorough examination of the dataset and objectives, it is evident that the five proposed models are the most suitable for the dataset. This research experiments with models ranging from the simplest, CNN, to the most complex, the Transformer model. Each model serves its own purpose and has distinct advantages. Below are the model architectures used in this study, including CNN, MobileNet, EfficientNet, and Transformer.

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 48, 48, 16)	448
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 16)	0
conv2d_4 (Conv2D)	(None, 16, 16, 32)	4,640
max_pooling2d_3 (MaxPooling2D)	(None, 5, 5, 32)	0
conv2d_5 (Conv2D)	(None, 3, 3, 64)	18,496
flatten_1 (Flatten)	(None, 576)	0
dense_2 (Dense)	(None, 64)	36,928
dense_3 (Dense)	(None, 1)	65

Fig 6. CNN architecture

upon a concept called "compound scaling." This concept addresses the longstanding trade-off between model size, accuracy, and computational efficiency. The idea behind compound scaling is to scale three essential dimensions of a neural network: width, depth, and resolution [20].

Multi-Input Model: The model is constructed with two main input components: Image Input: A tensor with dimensions (50, 50, 3), representing an image of size 50x50 with 3 color channels (RGB). Coordinate Input: A tensor with dimensions (2), representing the 2D spatial coordinates of the image.

Image preprocessing steps include: Randomly adjusting the brightness of the image (RandomBrightness). Randomly flipping the image (RandomFlip). Adding Gaussian noise to the image (GaussianNoise).

EfficientNetB3 Base Model: After preprocessing, the image is passed through the EfficientNetB3 base model to extract important features. The EfficientNetB3 model is loaded with pretrained weights from the ImageNet dataset.

Top model layers are added to the output of the base model for classification. Specifically: Two Dense layers with ReLU activation functions are used to extract complex features from the output of the base model. Three BatchNormalization layers are used to stabilize and accelerate the training process. Dropout layer is used to prevent overfitting. The final layer is a Dense layer with a sigmoid activation function, generating binary classification predictions [21].

The model is compiled with two inputs (image and coordinate) and one output (classification prediction). The training process uses binary_crossentropy loss function and is optimized using the Adam optimization algorithm with a learning rate of 0.001. Metrics used to evaluate performance include accuracy.

3. MOBILENET ARCHITECTUE

The MobileNet model is built upon a deep convolutional neural network (CNN) for image classification [17]. Here is a description of the MobileNet model architecture:

Load pre-trained model: Use the 'MobileNet' function to create a pre-trained CNN model with default weights, excluding the top layer (include_top=False), and the input shape defined by the 'inputShape' parameter.

Add custom layers at the output of the model to perform classification. Specifically: Use the 'GlobalAveragePooling2D' layer to extract features from the output of the CNN model. Add a 'Dense' layer with 1024 neurons and ReLU activation function to create a dense neural network representation. Apply a 'Dropout' layer with a dropout rate of 0.6 to prevent overfitting. Use a final 'Dense' layer with the number of outputs as 'numClasses' and softmax activation function for classification.

1. CNN ARCHITECTUE

Mô hình CNN đơn giản với đầu vào là một lớp Conv2D với 16 kernel kích thước 3*3, đầu vào là một hình ảnh kích thước 50*50*3. Tiếp theo là một lớp Maxpooling2D, sau đó là một lớp Conv2D và Maxpooling2D, một lớp Conv2D rồi đến lớp Flatten. Cuối cùng là lớp kết nối đầy đủ gồm hai lớp Dense. Lớp Dense thứ nhất chứa 64 nốt và lớp Dense thứ 2 chứa một nốt và hàm kích hoạt là sigmoid trong khi các lớp Conv2D là ReLU.

3. EFFICIENTNET ARCHITECTUE

EfficientNet is a convolutional neural network built

Combine base model with custom top layers: Merge the CNN model created from step 1 and the custom layers from step 2 to create the complete model. This model has a structure from the input of the CNN model to the output of the classification layer.

4. TRANSFORMER ARCHITECTURE

The MobileNet model is created by combining a pre-trained CNN with custom layers to classify images into `numClasses` classes. This structure has been proven effective in various computer vision applications.

The Transformer follows this overall architecture using stacked self-attention and pointwise, fully connected layers for both the encoder and decoder, shown in the left and right halves of Fig 9, respectively [16]

Encoder: The encoder is composed of a stack of $N = 6$ identical layers. Each layer has two sub-layers. The first is a multi-head self-attention mechanism, and the second is a simple, positionwise fully connected feed-forward network. We employ a residual connection [18] around each of the two sub-layers, followed by layer normalization [19]. That is, the output of each sub-layer is $\text{LayerNorm}(x + \text{Sublayer}(x))$, where $\text{Sublayer}(x)$ is the function implemented by the sub-layer itself. To facilitate these residual connections, all sub-layers in the model, as well as the embedding layers, produce outputs of dimension $d_{\text{model}} = 512$ [16].

Decoder: The decoder is also composed of a stack of $N = 6$ identical layers. In addition to the two sub-layers in each encoder layer, the decoder inserts a third sub-layer, which performs multi-head attention over the output of the encoder stack. Similar to the encoder, we employ residual connections around each of the sub-layers, followed by layer normalization. We also modify the self-attention sub-layer in the decoder stack to prevent positions from attending to subsequent positions. This masking, combined with fact that the output embeddings are offset by one position, ensures that the predictions for position i can depend only on the known outputs at positions less than i [16].

Attention An attention function can be described as mapping a query and a set of key-value pairs to an output, where the query, keys, values, and output are all vectors. The output is computed as a weighted sum of the values, where the weight assigned to each value is computed by a compatibility function of the query with the corresponding key [16].

The Transformer architecture has demonstrated effectiveness and scalability in processing natural language data. Thanks to the self-attention mechanism, this model can capture complex relationships in language, leading to significant improvements in tasks such as machine translation and text summarization.

5. PYTHON GRAPHICAL USER INTERFACE - TKINTER

After completing the training and selecting the best-performing model, this project proceeded to build a Graphical User Interface (GUI) application with the aim of enhancing applicability and facilitating user interaction. Fig 10 is the schematic diagram of the graphical user interface design.

First, there will be a welcome interface where users can perform predictions on a test dataset across all slices. When the Predict button is clicked, the interface will transition to a page where users can enter detailed patient information and save the patient's information. This will be convenient for accessing data later after making predictions, if necessary. Next is the function to load a directory, where the directory should have a file structure similar to the dataset. This can be customized, but for this project, a simple approach will be presented. After successfully loading the necessary information, the next step is to perform analysis. Here, the program will load

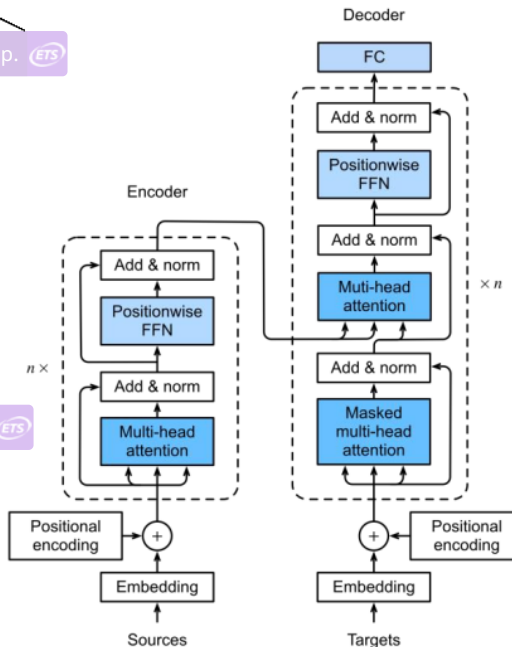


Fig 9. Transformer architecture model

the trained model into the program and analyze the selected directory to see if it exists or not. At this step, the analysis will also be conducted to determine how many files and directories are found. Simultaneously, all data in that directory will be processed. Then, data will be loaded, analyzed, and visualized before prediction. These images will be converted into a standard format that the model can predict. Next, they will be fed into the model for analysis, resulting in an array of predictions. At this point, the output needs to be processed to match the correct format. After obtaining the output, data visualization will be performed to compare the results with the original ones. Finally, all results will be returned to the result interface, displaying the details of the data analysis and predictions. To handle this, **multithreading** in Python will be used to increase prediction efficiency. This means that while the data analysis process is ongoing, data will also be preprocessed and the model will be loaded. After all processes are completed, a thread will wait for the others to finish executing before returning the results. This ensures that the window displaying the analysis and processing progress is shown. After displaying the result window, users can return to the INPUT interface to continue the process if desired.

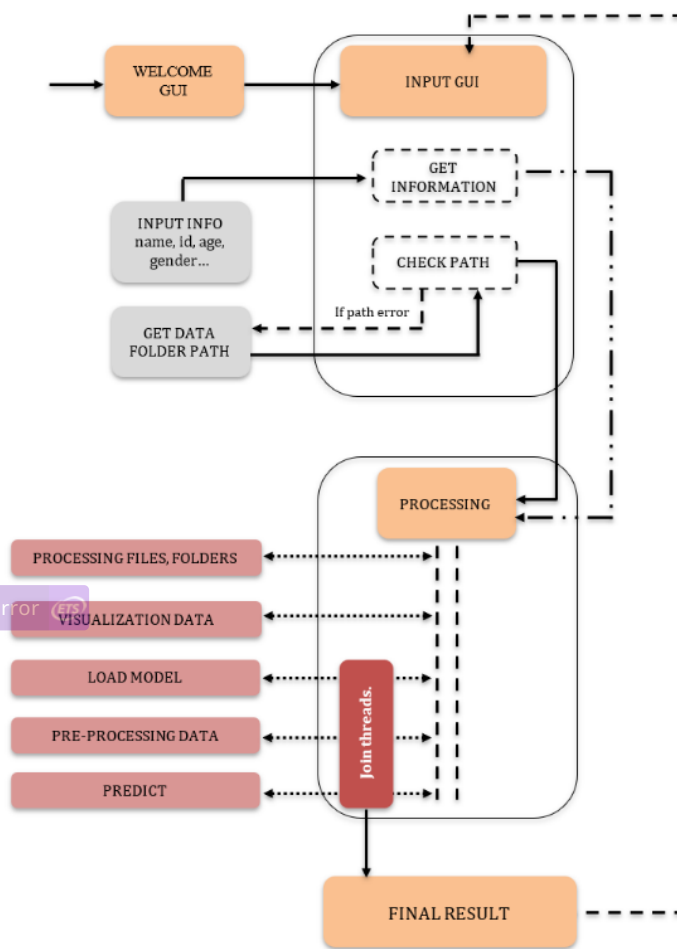


Fig 10. The system diagram of breast cancer detection user interface

6. ACTIVATION FUNCTIONS

This research utilizes the ReLU (Rectified Linear Unit) and Sigmoid activation functions. For the ReLU activation function, when the inputs are non-negative, they remain unchanged, while negative values are set to 0. The ReLU function is used at the outputs of the nodes between hidden layers. The sigmoid function is used at the final output to classify the probability of an output belonging to class 0 (negative) or class 1 (positive). Table 1 below shows the formulas for the ReLU and Sigmoid functions.

Table 1. Activation functions

ReLU	Sigmoid
$F(x) = \text{Max}(0, x)$	$F(x) = \frac{1}{1 + e^{-x}}$

Using ReLU and Sigmoid activation functions helps in nonlinear transformations of the input data and in capturing complex patterns, which are essential for effective deep learning models.

For the ReLU activation function, when the inputs are non-negative, they remain unchanged while negative values are set to 0. The ReLU function is used at the outputs of the nodes between hidden layers. The sigmoid function is used at the final output to classify the probability of an output belonging to class 0 (negative) or class 1 (positive).

7. THE PERFORMANCE EVALUATION METRICS OF THE MODEL

After constructing the models, deployment and training of the models are carried out, followed by evaluating the performance of each model on the same test dataset. Once the best metrics for each model are obtained, the model with the highest accuracy and best performance is selected. In this study, four methods are used to evaluate the performance of the model: accuracy, precision, recall, and f1-score.

Table 2. The performance evaluation metrics of the model

Accuracy	Precision	Recall	F1-score
$\frac{TP + TN}{TP + TN + FP + FN}$	$\frac{TP}{TP + FP}$	$\frac{TP}{TP + FN}$	$\frac{2 * precision * recall}{precision + recall}$

In which:

- True positive (TP): Instances belonging to the positive class that the model correctly predicts as positive.
- True negative (TN): Instances belonging to the negative class that the model correctly predicts as negative.
- False positive (FP): Instances belonging to the negative class that the model incorrectly predicts as positive.
- False negative (FN): Instances belonging to the positive class that the model incorrectly predicts as negative.

Accuracy calculates the proportion of correct labels over the total predicted labels. Precision answers the question of how many correct predictions there are among the cases predicted as positive. A model with high precision accuracy means that the model performs well on the positive class. Recall measures the proportion of accurately predicted positive cases over all samples belonging to the positive class. F1-score is the harmonic mean between precision and recall. Therefore, it provides a better representation in evaluating accuracy simultaneously on both precision and recall [14].

VI. RESULT AND DISCUSSION

On the same dataset, image parameters varied and were adjusted multiple times. However, it can be observed that the EfficientNet model achieved the best performance on both the training and testing datasets, with an accuracy of 93% on the training data and 90% on the testing data. Following that, the transformer model achieved an accuracy of 94% on the training dataset and 85% on the testing dataset. These two models exhibited high accuracy due to their complexity and ability to learn important features from the data; however, there is still room for improvement in these metrics. Next is the CNN model, with an accuracy of 88% on the training data and 70% on the testing data. This figure is relatively modest, as the CNN model is designed to be relatively simple and requires further improvement in the future. Lastly, the MobileNet model achieved an accuracy of... on the training data and ... on the testing data.

Table 3. Accuracy and validation accuracy of models

Model	Accuracy	Val_accuracy
CNN	88%	70%
MobileNet	85%	82%
EfficientNet	93%	90%
Transformer	94%	85%

After comparing the models based on accuracy, the potential models used for evaluation on the testing data are the EfficientNet and Transformer models. However, the EfficientNet model exhibited better performance. Fig 11 is the loss curve of the EfficientNet model. The model converged relatively quickly and achieved a good threshold in the later stages. In this study, the decision to use the EfficientNet model as the chosen model was made because it demonstrated the best performance compared to the other models on the testing dataset. All evaluation metrics of the model yielded quite impressive results.

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Fig 12 serves as an example of the experimental results of the EfficientNet model on the testing dataset. It can be observed that the model almost accurately predicts regions containing cancer cells, which is crucial for cancer

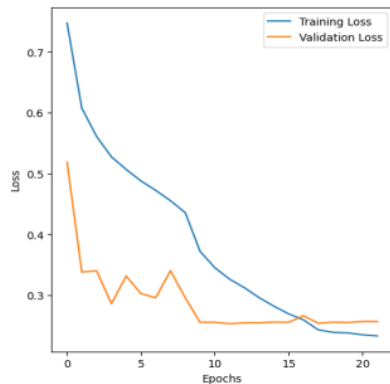


Fig 11. Loss and validation loss training

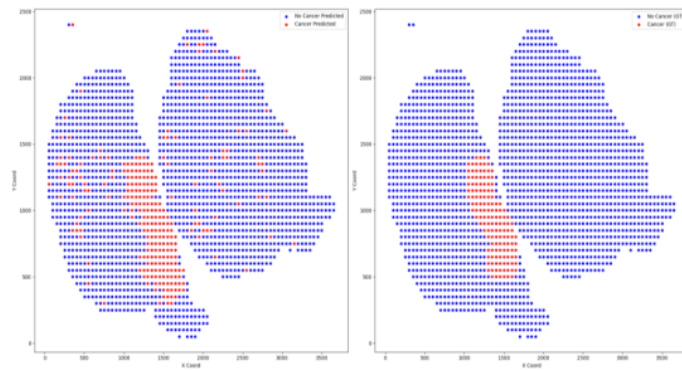


Fig 12. The image coordinates of the entire slice

detection. Neglecting cancer cells or making too many incorrect predictions may not support accurate diagnosis. Additionally, the model also makes some incorrect predictions for benign regions. However, this occurrence is minimal, and the most important aspect is that regions containing cancer cells are accurately predicted.

Fig 13 depicts the confusion matrix for the dataset after prediction. A total of 13,877 images were predicted, with 10,853 images correctly predicted and 3,024 images mislabeled. This indicates that the model tends to predict negative labels as positive ones.

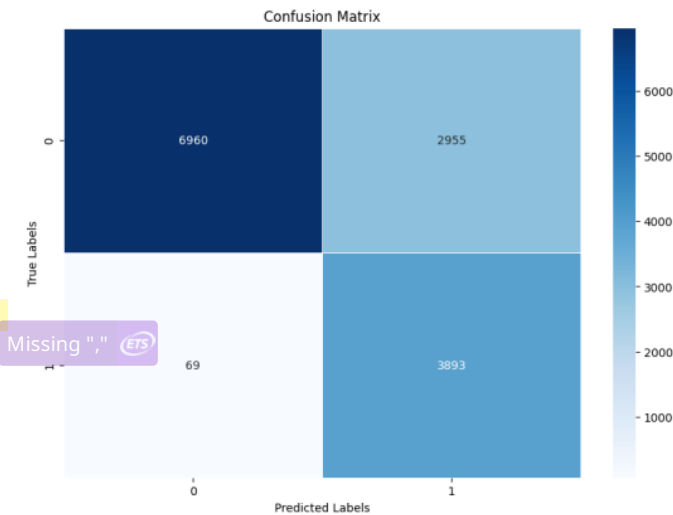


Fig 13. Confusion matrix on the testing data

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VII. CONCLUSION AND FUTURE SCOPE

In this project, we have successfully applied deep learning models to detect breast cancer images, perform analysis, and make predictions on new data. At the same time, we have developed a graphical user interface using tkinter. However, continued research and improvement of the model's accuracy are necessary. We will continue to modify and experiment with different structures, parameters, and models to find the best model and enhance its performance, ensuring accuracy when deployed in real-world scenarios. Although successful in building deep learning models and applying them to detect images containing cancer cells, the performance of the models has not yet achieved satisfactory results on the test dataset. The reason may be due to the insufficient number of epochs trained and the need to adjust the threshold appropriately to yield better results.

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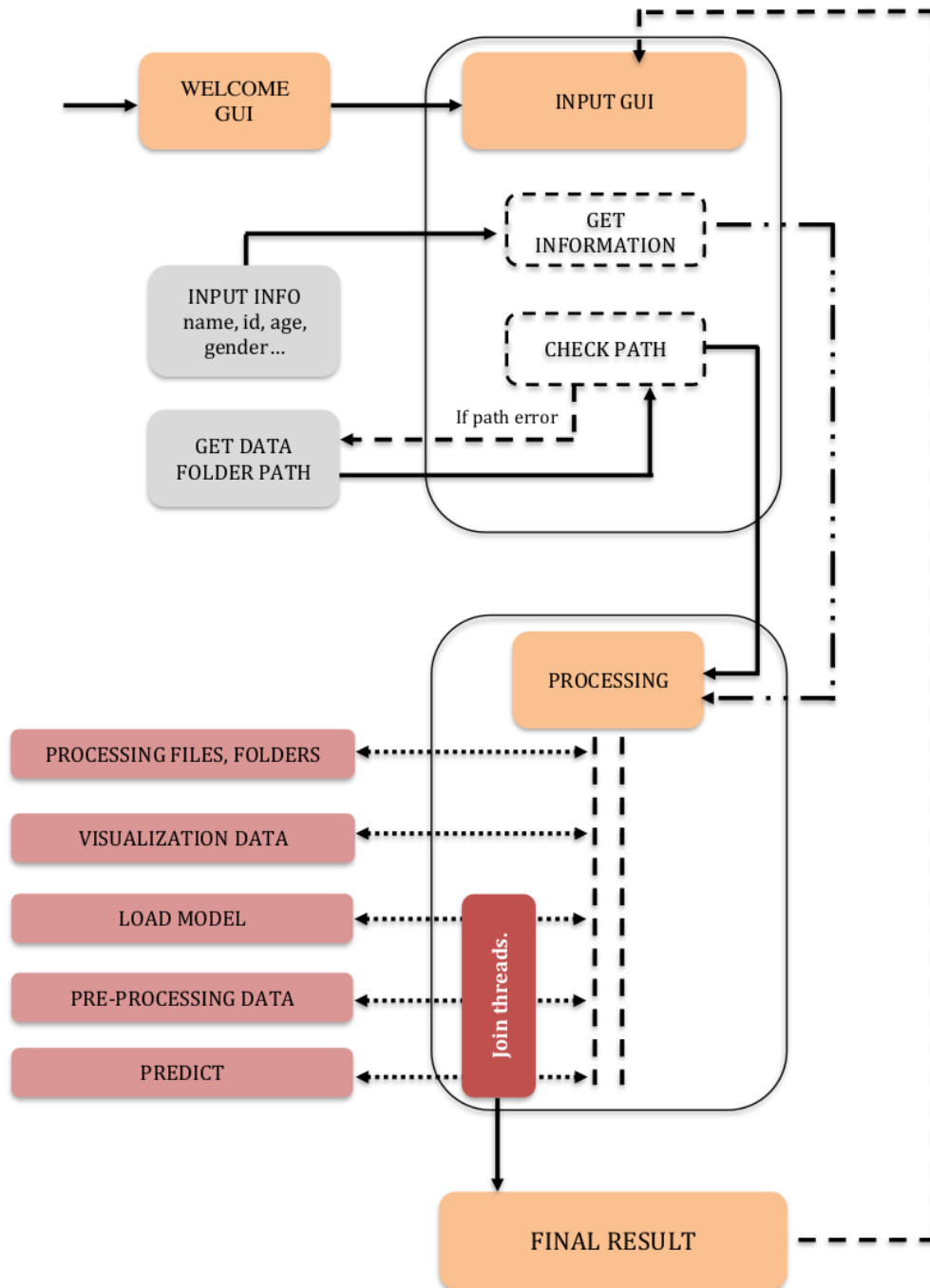
The success of applying deep learning in classifying images containing cancer cells heavily relies on the model. Improving the performance and accuracy of the model is crucial. In future research, it is necessary to adjust some model parameters, vary the number of training epochs to increase accuracy and model performance. Additionally, exploring, experimenting, and developing new models with higher applicability, enhancing existing models, and exploring new directions in data preparation and processing methods are essential to contribute to improving the model's performance. Simultaneously, enhancing the user interface and expanding functionalities to improve data processing, detection, and storage after analysis are also necessary for further refinement.

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