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RESEARCH ARTICLE

FastLeakyResNet-CIR: A Novel Deep Learning Framework for Breast Cancer Detection and Classification

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ABSTRACT Breast cancer is a type of disease that primarily affects the breast tissue, and it is crucial to achieve early diagnosis for successful treatment and recovery. In recent years, the residual network (ResNet) has gained significant attention in the detection of breast cancer using medical images. In this paper, we propose an efficient and robust deep learning framework called FastLeakyResNet-CIR, an improved ResNet architecture, for breast cancer detection and classification. The FastLeakyResNet-CIR achieves an impressive accuracy of 98.94% when evaluated on a dataset of 7909 microscopic images of breast tumor tissue from BreakHis dataset, which outperforms the state-of-the-art methods, e.g. ResNet18, ResNet50, InceptionV3 and VGG16. The experiment results further highlight the potential of FastLeakyResNet-CIR for accurate and rapid diagnosis of breast cancer, thus facilitating effective medical treatment for patients.

INDEX TERMS Breast cancer, convolutional neural network, FastLeakyResNet-CIR, medical image classification, residual network.

I. INTRODUCTION

Breast cancer poses a significant risk to women's lives and overall health, making it a pressing concern. Globally, breast cancer stands out as one of the most commonly diagnosed forms of cancer among women [1], [2], [3], [4], [5]. Egypt, in particular, has witnessed a rapid rise in cancer case, with breast cancer being prominently affected. Detecting breast cancer at an early stage plays a pivotal role in ensuring effective treatment and reducing mortality rate.

Several diagnosis techniques have currently been employed for early detection of breast cancer [6], such as mammography, thermography, ultrasound, and magnetic resonance imaging (MRI). Mammography is one of the most popular methods because of the relative high-accuracy, low-cost, and high detectability, which is able to provide an effective imaging tool for breast cancer identification and classification [7]. However, the performance of mammography may be weak in some cases, especially in patients with dense breast tissue [8]. Thermography is an emerging breast cancer screening technology by analyzing a thermogram obtained by a thermal infrared camera. It is characterized by radiation-free, low-cost, and non-invasive. Compared with mammography, breast thermography has its own advantages including its ability to applicable to individuals with dense breast tissue and effectiveness for all age women [9]. Therefore, thermography is regarded as a safe, quick and effective early diagnosis technique for patients with breast cancer. Ultrasound is a primary tool for breast cancer screening, which provides a potentially

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viable solution for early breast cancer detection because it is easy to carry, and low cost than mammography [10]. It plays a crucial role in differentiating between solid-cystic breast lesions and characterizing solid lesions. Thanks to technological advances, high-frequency ultrasonography probes have enabled the visualization of even small breast lesions, especially for patients with dense breast [11]. Therefore, it is the ideal imaging tool to guide subsequent procedures. Magnetic resonance imaging is primarily utilized as a supplemental means to breast cancer screening along with mammography or ultrasound [12]. Since 2000, the breast MRI, with excellent sensitivity and specificity, has become an important tool in high risk screening and diagnosis for earlier-stage breast cancer by measuring the size of the cancer, and looking for other tumors in the breast. Recent research has found that the MRI is capable of locating some small breast lesions that may be sometimes missed by mammography [13], thus, the MRI has been extensively used for patients with newly diagnosed breast cancer.

Nowadays, the methods based on deep learning (DL) have been extensively applied to medical image analysis and breast cancer diagnosis [14], [15], [16]. Convolutional neural network (CNN) is one of the most popular approaches in DL [17], [18], which achieves an end-to-end mapping learning from input image to output result and becomes an efficient classification model [19]. Subsequently, a variety of DL models are emerging, such as RNN, AlexNet, GoogleNet, ResNet, VGG, and U-Net. Tan et al. [20] utilized CNN acting on mammogram imaging system to produce three classifications of normal, benign and malignant, which assists specialist to diagnosis and classify the breast cancer quickly. Mambous et al. [21] developed a deep neural network (DNN) model that is related to pre-trained Inception V3 model for sick and healthy breast classification, where they pay attention to the physical model camera sensitivity of breast. Ting et al. [22] presented a convolutional neural network improvement for breast cancer classification (CNNI-BCC), which can classify breast cancer medical images into healthy, benign and malignant patients in the context of no prior information about cancerous lesion. It improves the breast cancer lesion classification and helps experts for breast cancer identification. Barbosa et al. [23] introduced the deep-wavelet neural network (DWNN) for feature extraction in image representation, combining it with intelligent algorithms for pattern recognition. They demonstrated a sensitivity of 95% and specificity of 79% using the DWNN for detection of breast lesions in thermographic images. While promising, there are some limitations about the DWNN approach. It relies on handcrafted feature extraction, which may not capture discriminative features as effectively as end-to-end feature learning methods like CNNs. Also, their evaluation was on a small proprietary dataset, so further validation on larger benchmark datasets would be needed. Naseem et al. [9] proposed a computer-aided detection approach based on CNN using thermal images, it is faster, reliable and robust, and obtains a higher accuracy (92%) and F1-score (92%) that outperforms several architectures, e.g. ResNet 50, SeResNet 50 and Inception. Mohiyuddin et al. [24] put forward a modified network of YOLOv5 to detect and classify breast tumors, and it performs better than YOLOv3 and faster regions with CNN (RCNN) with lowering the false positive ratio (FPR) and false negative ratio (FNR) and boosting the Matthews correlation coefficient (MCC) value. Asadi and Memon [25] employed a cascade network with U-Net for segmentation and a ResNet for efficient breast cancer detection, which has a classification accuracy of 98.61% and F1 score of 98.41%.

To improve the accuracy and interpretability of breast cancer detection and classification, we propose a novel deep learning framework called fast leaky residual network with class imbalance reduction, termed as FastLeakyResNet-CIR, which has higher accuracy and faster convergence rate. The main contribution of this study is as follows.

(1) The novel scheme FastLeakyResNet-CIR is presented for predicting breast cancer.

(2) We strengthen the robustness of the model by introducing the improved loss function and improved Adam algorithm.

(3) The proposed method performs well in a performance comparison against the state-of-the-art breast cancer prediction methods.

The rest of the paper is organized as follows. Section II provides the theoretical basis. Section III introduces a detailed description of the proposed breast cancer detection scheme. Section IV presents the experiments and results. Section 5 gives the conclusions.

II. METHODOLOGY

Figure 1 shows the details of the proposed breast cancer detection scheme that consists of three main steps. First, the data preprocessing aims to reduce training time, enhance image, alleviate overfitting and learn feature, which includes several techniques such as resizing and balance, Gamma transform, data augmentation and shuffling and splitting. Second, the FastLeakyResNet-CIR is designed to predict breast cancer. Third, the improved loss function and improved Adam algorithm are introduced to strengthen the robustness of the model.

A. DATA AND PROCESSING

1) RESIZING AND BALANCE

In this study, we utilize the BreaKHis dataset, Breast Cancer Histopathological Database, to validate the proposed scheme. The dataset was previously used by Spanhol et al. [26], which contains 7909 breast cancer histopathology images acquired on 82 patients with two states benign and malignant. Since the number of normal training sets is much smaller than the number of abnormal training sets in the dataset, we replicate the normal training sets itself to be the same as the number of the two training sets. To cut down the data size, all images are resized to 224*224 before training, which will significantly reduce the training time of the model.

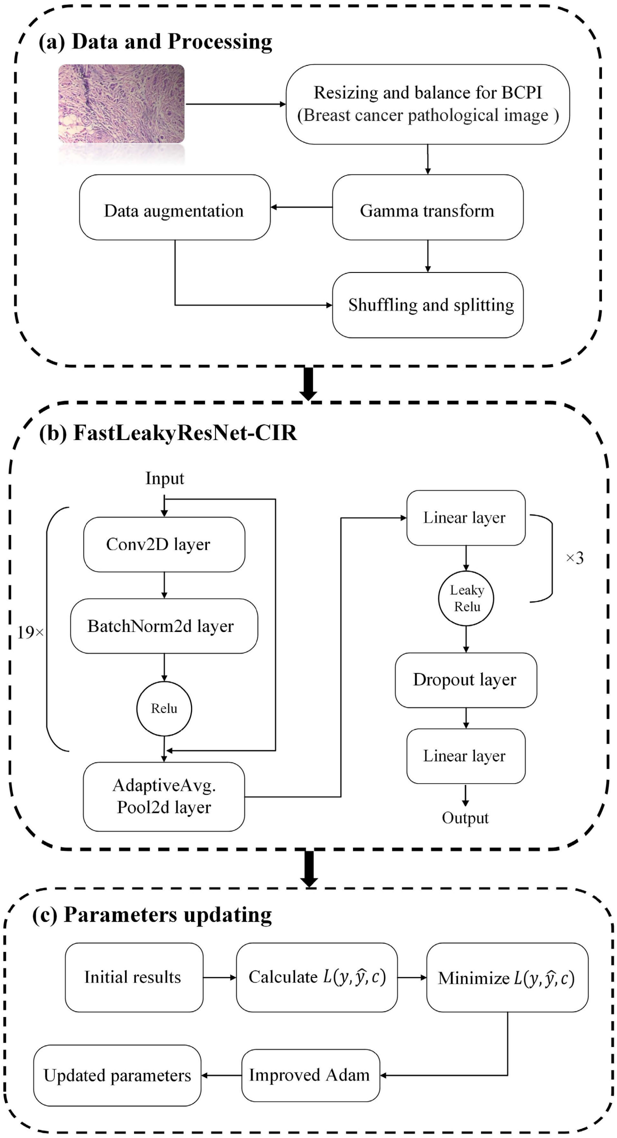


FIGURE 1. **Illustration of the breast cancer detection scheme, (a) breast cancer data preprocessing, (b) a FastLeakyResNet-CIR, and (c) parameters updating strategy.**

2) GAMMA TRANSFORM

The Gamma transform is employed for image enhancement, which boosts the overall brightness of the image in the darker detail and increases the contrast at lower grey level, making it easier to distinguish image detail at lower grey value. During the experiment, the gray value of the images in the training sets is low, but the results can be effectively enhanced by setting the gamma value to 0.7, so as to improve the training accuracy of the model. The comparison before and after Gamma transform is shown in Figure 2.

3) DATA AUGMENTATION

Data augmentation is a powerful means that helps expose the model to various transformations and variations commonly found in real-world data. By randomly rotating, translating, scaling, and flipping the original images, we effectively expand the dataset and provide the model with a richer set of training examples. This approach allows the model to learn robust features that are invariant to these transformations, improving its ability to generalize well to unseen data. The increased diversity through data augmentation is beneficial to alleviate overfitting and enhance the model's performance across different scenarios and conditions.

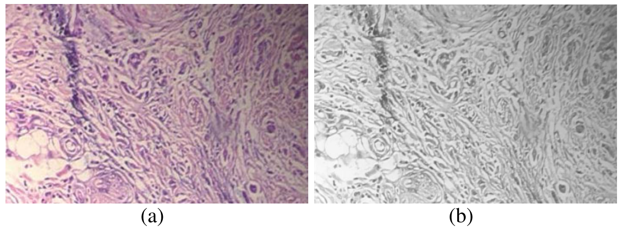


FIGURE 2. **(a) The image before Gamma transform and (b) the image after Gamma transform.**

4) SHUFFLING AND SPLITTING

Shuffling is able to prevent model oscillation during the training, which is beneficial for the robustness of the model. Moreover, it can also hinder overfitting and help the model learn more correct features. Therefore, it's necessary to shuffle the dataset. Then, we divide the dataset into training set, validation set and test set in the ratio of 8:1:1.

B. NETWORK ARCHITECTURE AND IMPLEMENTATION

The FastLeakyResNet-CIR, an improved ResNet, is designed for breast cancer detection, constructed by four convolutional blocks, adaptive average pooling layer, linear layer and output layer. Each convolutional block is comprised of five convolutional layers with the sizes of 3 × 3 × 64, 3 × 3 × 128, 3 × 3 × 256 and 3 × 3 × 512, respectively, which gradually extract more sophisticated features. The adaptive average pooling layer is applied to reduce the spatial dimension of the feature map, enhance the robustness of the model and make it suitable for the image with varying size. The LeakyReLU as an activation function enables the model to have good nonlinearity and generalization abilities. In addition, the ResNet residual blocks with skip connection help to train the model efficiently and prevent the vanishing gradient when increasing the network depth. The output layer has two states, benign and malignant, which are represented in binary as 1 or 0. The structure of FastLeakyResNet-CIR is shown in Figure 3.

C. PARAMETERS UPDATING

1) LOSS FUNCTION

In binary classification task, the loss function based on cross-entropy is widely used, which is defined as follows:

$$L(y, \hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)) \quad (1)$$

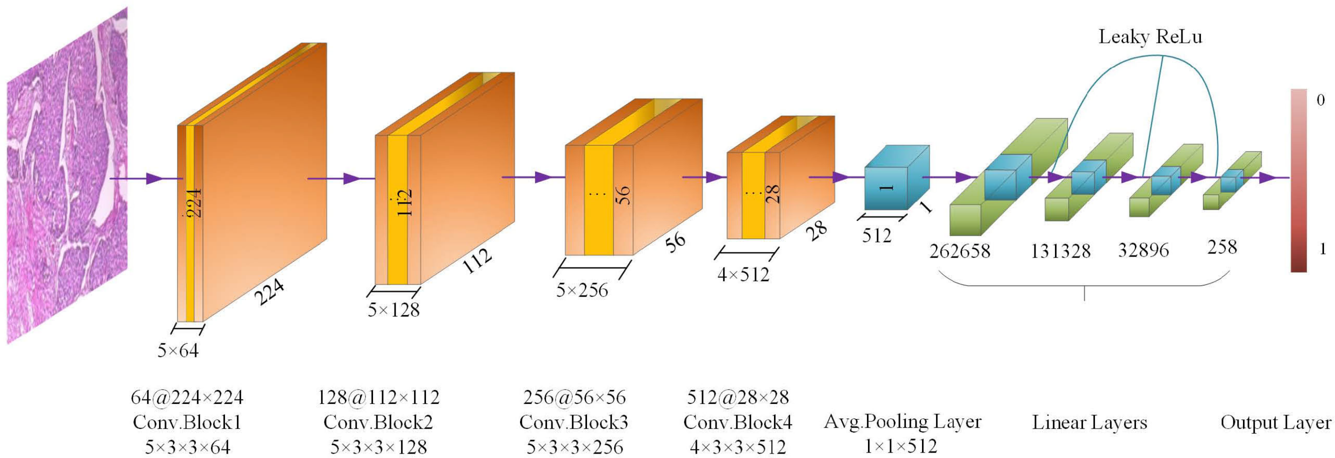


FIGURE 3. **Proposed FastLeakyResNet-CIR framework designed for breast cancer detection.**

where N represents the number of samples, L is loss function, y and $\hat{y}$ denotes the true value and predicted value, respectively.

However, the traditional loss function suffers from some drawbacks, for example, 1) it does not cope well with imbalanced data, resulting in a bias towards the majority samples and far from the minority samples; 2) it does not make full use of confidence information, lacking targeted penalty for uncertain samples; 3) it does not impose the constraints on the complexity of the model, leading to potential overfitting. The above-mentioned issues may degrade the performance of the model when dealing with imbalanced data and uncertain samples, and the ability of generalizing to new data.

In the paper, we introduce the category weights, confidence penalty and L1 regularization into the above loss function, thus, Eq. (1) can be rewritten as:

$$\begin{aligned} L(y, \hat{y}, c) &= -\frac{1}{N}\sum_{i=1}^{N}(\omega_{malignant} \bullet y_i \log(\hat{y}_i) \\ &\quad + \omega_{benign}(1-y_i)\log(1-\hat{y}_i)) + \lambda H(c,t) + \alpha \bullet \|w\|_1 \end{aligned} \tag{2}$$

where the weights of malignant samples and benign samples are $\omega_{malignant}$ and ω_{benign}, respectively, c is the predicted confidence, t is the threshold, $H(\bullet)$ is the penalty term and the corresponding weight is λ, $\|\bullet\|_1$ denotes $L1$ regularization term and the corresponding weight is α, w is the weight vector parameter.

By employing category weights, we can improve the problem of class imbalance, and enhance the impact of breast cancer samples in the optimization process. Considering confidence information, we can strengthen the robustness and stability of the proposed model. Introducing a $L1$ regularization term, we can promote the model's generalization ability and prevent the overfitting. We introduce category weights $\omega_{malignant}$ and ω_{benign} in the loss function to account for class imbalance between malignant and benign samples. The motivation is to give more influence to minority malignant samples during training. By assigning a higher weight $\omega_{malignant}$ to losses on malignant samples, we increase their contribution to update the model parameters. This counters the tendency of overwhelmed malignant examples. The exact values can be tuned as a hyperparameter, with common choices being the inverse class frequencies or a fixed rebalancing ratio. The λ weight for the confidence penalty is set to 0.1 based on preliminary experiments. As a result, we obtain a detection model for breast cancer that focuses more on important class, possesses robustness, and performs well on unseen data.

2) OPTIMIZER

Adam (Adaptive Moment Estimation), proposed by Kingma and Ba [27], is an optimizer for optimizing stochastic gradient descent algorithm for neural network, which can be seen as a combination of Momentum and RMSProp.

The traditional Adam algorithm ignores the stability of gradient and only considers the first-order and the second-order moment estimation. It may cause suboptimal learning rate when dealing with gradient that exhibits high variance or instability. Secondly, the Adam lacks personalized learning rate adjustment, because it utilizes fixed decay rate or step to adjust the learning rate without taking into account the difference in parameter importance or sensitivity. Thirdly, the Adam relies only on global statistical information and fails to adequately consider the feature of each individual batch.

In the paper, we bring some improvements to the traditional Adam algorithm as follows.

1) Computing the gradient g_t for the current step.

2) Calculating the stability term s_t, which is the standard deviation of the gradient plus a small constant.

Algorithm 1 Improved Adam

Input :
α : Step size;
β_1,$\beta_2 \in [0, 1)$: Exponential decay rates for the moment estimate;
(θ): Stochastic objective function with parameter θ.
Output : θ_t : Resulting parameter.
Initial parameter vectorθ_0
$m_0 \leftarrow 0$ (Initialize first moment vector)
$v_0 \leftarrow 0$ (Initialize second moment vector)
$t \leftarrow 0$ (Initialize time step)
while θ_t not converge do
$t \leftarrow t + 1$
$g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ (Get the gradient of the current step)
$m_t \leftarrow \beta_1 m_{t-1} + (1 - \beta_1) g_t$ (Update first moment estimate)
$v_t \leftarrow \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$ (Update second moment estimate)
$m_t' \leftarrow m_t/(1 - \beta_1^t)$ (Compute bias-corrected first moment estimate)
$v_t' \leftarrow v_t/(1 - \beta_2^t)$ (Compute bias-corrected second moment estimate)
$s_t \leftarrow \sqrt{v_t'} + \varepsilon$ (Compute the stability term)
$\rho_t \leftarrow \frac{g_t}{s_t}$ (Compute the gradient stability ratio)
$\alpha_t \leftarrow \alpha \bullet \max(0, 1 - \rho_t)$ (Compute the adjusted learning rate)
$\theta_t \leftarrow \theta_{t-1} - \alpha m_t'$ (Update parameters with adjusted learning rate)
end while

3) Calculating the gradient stability ratio ρ_t by dividing the gradient by the stability term.

4) Computing the adjusted learning rate α_t based on the gradient stability ratio.

5) Updating the parameter θ_t by means of the adjusted learning rate.

Algorithm 1 describes the improved Adam algorithm.

We compute s_t as the standard deviation of gradient g_t plus a small constant ε. Using the standard deviation can quantify the dispersion of gradients, allowing us to gauge the level of noise. The constant ε (set to $1e - 8$) ensures numerical stability when the variance is near zero. By incorporating s_t, we can adjust the learning rate according to the stability of the gradients. Parameters with noisy gradients are assigned lower learning rates to smooth the updates. This provides a personalized learning rate adaptation for each parameter tailored to the stability of its gradients. We introduce an adjusted learning rate α_t based on the gradient stability ratio ρ_t. The motivation is to scale the learning rate for each parameter according to the stability of its gradient. Parameters with noisy gradients get assigned a lower learning rate for that iteration to dampen the update steps. This allows for more personalized and adaptive tuning of the learning rate, as opposed to using a single global value. Setting the learning rate based on ρ_t provides a data-driven way to stabilize training and accelerate convergence by smoothing out fluctuations in the gradient.

In this experiment, we use CUDA in the PyTorch framework based on RTX 3090 GPU for training to ensure the speed and accuracy of the model. The epoch is set to 60, batch size is 64, and the initial learning rate is set to 0.03. The training process will take earlystop action when no improvement occurs in the loss of the validation set.

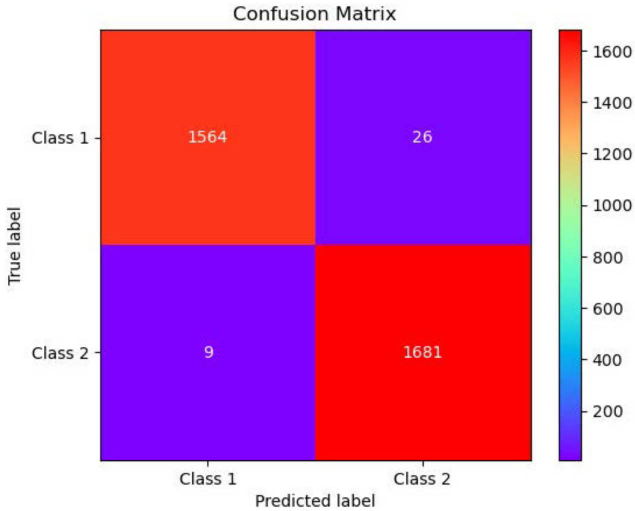


FIGURE 4. Confusion matrix of FastLeakyResNet-CIR on test set.

TABLE 1. Comparison with some classic models.

Model	Accuracy	Precision	Recall	F1score
FastLeakyResNet-CIR	98.94%	99.43%	98.36%	98.89%
ResNet50	92.63%	94.83%	89.69%	92.19%
InceptionV3	91.23%	91.07%	90.82%	90.94%
ResNet18	86.14%	87.63%	83.14%	85.33%
VGG16	79.45%	78.55%	79.25%	79.90%

III. RESULT AND EVALUATION

This section provides a detailed description of the experiment results to verify the performance of the proposed FastLeakyResNet-CIR breast cancer detection method.

A. EVALUATION INDICATORS

In order to quantitatively assess the performance of the proposed model, the classification results are evaluated using four metrics including accuracy, recall, precision, and F1 score [7], which are defined as:

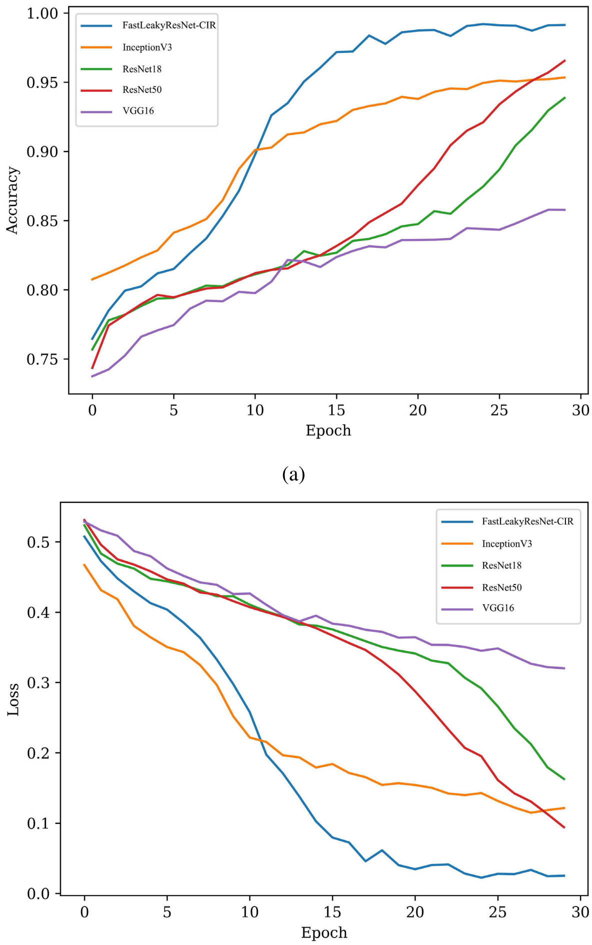
$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$F1score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

where TP is the true positive, FP is the false positive, FN is the false negative, and TN is the true negative. It is noted that the precision and recall is a pair of contradictory quantities, the former denotes the probability of predicting a positive case as a positive sample and the latter is the probability of predicting a true positive case as a positive sample. Thus, we employ the $F1score$ to examine the precision and recall of the model in a comprehensive way.



(a)

(b)

FIGURE 5. **Accuracy (a) and loss (b) comparison results obtained by five methods.**

B. RESULT AND COMPARISON

In this experiment, the iterative process of FastLeakyResNet-CIR is relative stable, and it converges at the 15th Epoch. The whole training process ends early at the 31st Epoch. The FastLeakyResNet-CIR achieves better classification accuracy, recall, precision, and F1-score values 98.94%, 98.36%, 99.43% and 98.89%, respectively, which illustrates the effectiveness of the proposed method for detecting breast cancer. Figure 4 shows the confusion matrix for the test phase of the proposed breast cancer detection framework. It can be clearly observed that the 3280 images are tested, 1590 samples are classified as normal, and 1690 samples are classified as abnormal. Among the normal samples, 1564 samples are correctly predicted as normal (TP), while 26 samples are incorrectly predicted as abnormal (FN). Furthermore, 9 abnormal samples are wrongly predicted as normal (FP), and 1681 abnormal samples are correctly predicted as abnormal (TN).

In addition, for further clarifying the superiority of the FastLeakyResNet-CIR, a comparison is made between the proposed method with some classical neural networks such as ResNet18, ResNet50, InceptionV3 and VGG16. We calculate the accuracy of each model on the test set and the corresponding convergence rate, and the results are shown in Figure 5. And, the accuracy, recall, precision, and F1 score values are listed Table 1. The comparison results indicate that the FastLeakyResNet-CIR has higher classification accuracy compared to other neural network models, therefore, it will have strong applicability in the field of physiological signal analysis. Meanwhile, it is noteworthy that the FastLeakyResNet-CIR converges around the 15th epoch because of improved loss function and improved Adam algorithm, which is significantly faster than other approaches, in other words, it can effectively reduce the time needed to train the model.

IV. CONCLUSION

In this study, we present a novel FastLeakyResNet-CIR model for breast cancer detection and classification. The proposed framework is composed of convolutional blocks, adaptive average pooling layer, linear layer and output layer. It reaches the highest classification accuracy of 98.94%. Also, the proposed breast cancer prediction scheme achieves an impressive score in a performance comparison against several classic breast cancer detection approaches. In addition, the FastLeakyResNet-CIR effectively solves the problem of class imbalance, avoids the overfitting and has good generalization ability and faster convergence speed by introducing the improved loss function and improved Adam algorithm, thus, it is a very promising and application-worthy deep learning model in the field of medical image analysis. In future work, data enhancement methods and breast cancer severity diagnosis will be explored.

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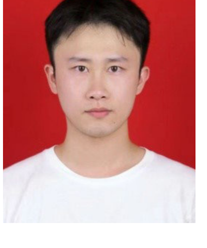

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