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An Efficient Methodology for the Classification of Invasive Ductal Carcinoma Using Transfer Learning

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Abstract: Currently, breast cancer (BC) is one of the leading causes of death in women. It is still a challenging task for the pathologist to diagnose cancer properly. In this research study, the communal kind of BC that's invasive ductal carcinoma (IDC) has been classified. For the classification of IDC, lots of developing techniques have been used in the medical research field. But many problems are faced regarding time to detect cancer cells in patients, class imbalance, data overfitting, less accuracy rate, and vanishing gradient in the BC classification technique. So, it is vital to develop an accurate, and well-organized system for the classification of IDC. To overcome these problems, an efficient methodology has been proposed in which we have defined the classification model as the TransResCNN model i.e. (transfer learning applied to the pre-trained residual network (ResNet) CNN model). Most popular transfer learning and data augmentation methods are applied for dealing with a huge dataset. For the performance evaluation, the model evaluates through a confusion matrix for image-based classification of IDC. Several evaluation metrics have also been applied like accuracy, precision, F1- score, and recall. A comparison of various existing studies performed with our proposed study shows that the proposed study achieved the highest accuracy of 90.76% and an F1-score of 93.56%. The investigated study shows that our proposed methodology achieved an improved performance than previous research studies.

Keywords: Breast cancer; Invasive ductal carcinoma; Transfer Learning; Convolutional neural network; A breast cancer classification; Breast histopathology images.

1. Introduction

In the present day, Cancer is also known as a fatal disease that is lead to death all over the world. Cancer is a potentially lethal disease that develops in living cells. The number of cancerous cells in the body increases daily. Ductal Carcinoma is the communal form of breast cancer (BC) that grows in the milk tube or ductus. Ductal carcinoma has further been divided into two subcategories that are invasive ductal carcinoma (IDC) and ductal carcinoma in situ (DCIS). Invasive Ductal carcinoma (IDC) grows in the ductus and spread throughout the breast tissues while ductal carcinoma in situ (DCIS) refers to the malignant growth of cancer cells in the ducts of milk. DCIS does not spread out from the breast tissue [1]. Early diagnosis is the most important step for BC patients to manage cancer in time. However, a patient's ignorance and improper treatment lead to cancer at a severe stage that may cause death. The World Health Organization (WHO) stated that cancer was the second-leading cause of death globally in 2022 and caused around 10 million deaths [2]. Many kinds of cancer occur in the human body such as cancer of the liver, bladder, stomach, lung, prostate, colorectum and breast cancer, etc. [3]. Despite the higher progress rate of survival in the medical research field, a BC comes at second rank which has lots of new cases arising quickly after lung cancer [4]. A report has also been made by International Agency for Research on Cancer (IARC), which shows that a total of 2,26,1419 new incidences of BC occur globally in 2020 in both males and females [5]. Breast cancer (BC) is a risky disease in women that cause death at a higher rate. A report has made in 2017 by the American cancer society that carcinoma cancer which is a communal kind of BC results in the deaths of almost 40,610 women and 460 men in the USA. Although the rate of survival is increasing by using the latest technologies that have played an important part in the prediction and proper diagnosis of breast cancer patients [6]. The American cancer society has recommended mammography for earlier detection of BC which reduces the risk factors of death and increases the survival rate.

Screening, Breast ultrasound, self-assessment, and Breast Magnetic Resonance Imaging (MRI) are common ways to earlier diagnose BC. However, these ways were sensitive and sometimes produce false-positive results [6],[7]. Digital pathology has an essential role in the medical field and modern clinical practice. High advancements in technology and the medical research field enabled the pathologist to work efficiently on whole-slide histopathology images with the ease of flexibility [8]. Lots of automated diagnosis systems developed for the precise prediction of BC. In the automated learning field traditional machine learning algorithm comprising SVM algorithm, random forest algorithm [9], K nearest neighbor procedure, Naïve Bayes, and decision tree algorithm [10] has an efficient and vital position in BC detection [11]. Evolving learning techniques like machine learning and image processing have also helped the competent progress of a CAD system to process efficiently on histopathological images for BC detection [12]. Although standard convolutional neural network based on deep learning has significantly worked for feature extraction purposes and played a dynamic part in the image classification of BC disease. Deep learning (DL) no doubt have performed great work in literature for carcinoma classification but due to variations and complexities in image datasets, feature selection was difficult.

The deep learning (DL) model was not suitable as it required an immense quantity of data for deep learning [40]. The deep learning technique was not reliable due to the high computation cost and higher training time rate [13]. For Carcinoma BC classification, lots of researchers are still working by using classical methods and technologies. But there are various problems and limitations in the existing research field of studies on carcinoma breast cancer (BC). The machine-learning algorithm was unsuitable for the timely detection of BC produced a poor result when training data has not present, was unsuitable for large datasets, and was non-effective on computer vision applications [15]. Transfer learning is another deep learning approach in the latest technology of innovative applications. Transfer learning has overcome data-lacking problems in the medical research field for automated classification of IDC histopathology images. However, there are many problems like class imbalance, overfitting, and less accuracy rate during the exposure and classification of carcinoma BC [16]. There is a need for an efficient system for the accurate and proper detection of carcinoma BC classification. Transfer learning can be beneficial to solve lots of existing problems. In this research work, we proposed an efficient methodology for automated and accurate classification of invasive ductal carcinoma (IDC) breast cancer by using transfer learning. For this purpose, the transfer learning technique with a pre-trained residual network (ResNet) is used for the classification of IDC. The experimental process is performed by using a publicly accessible breast histopathology images dataset. We have applied the data augmentation techniques to the training set for providing the solution to data overfitting, class imbalance, and large unseen dataset problems. We have selected the F1 score as the best evaluation metric to overcome the class imbalance problem.

To avoid the vanishing gradient problem, we have selected the unique neural network ResNet18 in our proposed methodology for the performance evaluation of the proposed model confusion matrix and other evaluation metrics such as accuracy, F1-score, precision, recall, true positive rate, false-positive rate, true negative rate, and the false-negative rate is also utilized. Lastly, the experimental result of our proposed methodology shows that we have achieved the 90.76% highest classification accuracy and 93.56% F1 score in comparison to existing research studies for the classification of IDC breast cancer using breast histopathology images dataset. Our proposed methodology improved the performance and also solve the various problems stated in the literature. To save time and reduce problems the main contribution of this study is given below:-

- Proposed an accurate transfer learning-based methodology for the classification of IDC breast cancer.
- Reduced the vanishing gradient, class imbalance, and overfitting problems while dealing with a large Dataset
- Applied transfer learning with a pre-trained ResNet18 model in combination with significant preprocessing steps to increase the classification performance
- Compare the result of our proposed methodology with previous research studies stated in the literature
- Achieved a result with vast improvement in accuracy and performance

In the rest of the paper, the research organization is as follows: section 2 explains the related work, section describes the proposed methodology, section 4 reviews the discussion of experimental results, finds the answer to the stated objective or research question, and compares the results of our proposed methodology with previous research studies. In the last section, we will state the conclusion and future work.

2. Related Work

Early diagnosis is the most important step for breast cancer (BC) patients to manage cancer promptly. In the medical imaging field, lots of problems occurred in image-wise assessment due to noisy images. In Machine learning (ML), data preprocessing has an essential step depending on the type of data. Most of the studies used mammography images to diagnose BC since preprocessing has basic steps involving cropping and resizing an image. Before training the classifier model various studies used different preprocessing techniques like normalization, image masking, thresholding, and feature extraction. In another study, the morphological operation was used for preprocessing followed by a support vector machine classifier [17],[18],[19]. Preprocessing makes the dataset compatible with a model so that model can accept all images. Preprocessing was applied to the BC histopathology images dataset to remove all variation and noise from image patches. Normalization technique used for preprocess method. Normalization helped for better quantitative analysis [20].

Model Provides better results when they were practiced on more data while using machine learning, deep learning, or transfer learning. Various techniques can be used for increasing the efficiency of a model by enhancing the data when practiced with more or unseen data. Lots of the researchers used data augmentation to increase the efficiency of the model. Common data augmentation techniques like width shift, height shift, rotation range, zoom range, and shearing were used in this state-of-the-art [16]. These data augmentation techniques were also used by Seemendra et al. [14] for automated BC classification. The researcher used a transfer learning approach with various pre-trained CNN models and achieved better accuracy 86.97% using the pre-trained DenseNet121 model with data augmentation and 84.94% accuracy without data augmentation. Their result demonstrates that by using data augmentation techniques, the model achieved higher accuracy as compared to without data augmentation another study, to solve the problem of overfitting data augmentation technique was used. Many deep neural networks address the challenges and issues as they required a large quantity of data for the training process. In previous studies, With deep neural network and training from scratch was not suitable for training model because of high computational cost, GPU limitation for large dataset training, Insufficient labeled images in the medical field, and lack of data [21],[22]. Another work by Romano AM et al. enhanced the deep learning approach used for predicting invasive ductal carcinoma (IDC) breast cancer histopathology images.

They have introduced a new pooling layer called accept reject pooling, with pooling sizes 2 by 2. Their results demonstrate a better result in percentage improvement of 11.5% and 0.86% for F1-score and balanced accuracy respectively [23]. By using various machine learning techniques Mohammed et al. analyzed BC detection. Researchers have proposed an approach that improved the performance and accuracy of three machine learning classifiers like decision trees, naïve Bayes, and sequential minimal optimization [24]. Hirra et al. have proposed a patch-based deep neural network model for the automated prediction of BC. Researchers classified breast cancer using histopathological images and reduced the overfitting problem by using weight decay [25]. In another experimental work by Alanazi et al., an automated detection system for BC was proposed. Researchers have worked on different layered CNN architecture and their result shows that CNN model 3 achieved accuracy with an improvement of 8% in comparison with the machine learning (ML) algorithm [26]. Another novel approach to discriminating invasive ductal carcinoma (IDC) breast cancer cells in WSI was proposed by the multi-level batch normalization technique. Their result achieved better accuracy in comparison with the original inception module [27]. A major task of an automated classification between cancerous and noncancerous cells in histopathology images was proposed by Reza & Ma et al. To enhance the productivity of CNN based classifier and to control the class imbalanced problem various oversampling and under-sampling techniques were used [28]. In another work by Siddiqui et al., deep learning techniques were used for the classification of malignant and non-malignant IDC tissues in whole slide images (WSI) [29]. Another system was proposed by Celik et al. for the automated detection of invasive ductal carcinoma (IDC). The proposed system used deep transfer learning ResNet50 and DenseNet-161 pre-trained models for the detection of IDC and non-IDC image patches [30]. In another study, Ahmed et al. used the transfer learning technique for the classification of whole-slide histopathological images. The researcher has utilized pre-trained VGG16 and InceptionV3 models for the automated feature extraction and classification of histopathological images. Their result showed that VGG16 achieved the accuracy with an improvement of 0.65 to 0.77 and for inceptionV3 model accuracy improved from 0.74 to 0.79. However, the large dataset and class imbalance problem was not properly solved which were the main limitation in this research field of study [31]. In other research work, the double transfer learning method was used by Matos et al. for the classification of BC histopathology images. With the ImageNet dataset, they utilized the inceptionv3 model for automated feature extraction from histopathology images. Transfer learning was also applied to SVM to filter the patches from BC histopathology images. Their results showed an improved classification accuracy of 3.7% by using inception V3 and 0.7% by using SVM [32]. While Veta et al. used a densely connected convolutional network for the prediction of invasive ductal carcinoma (IDC) breast cancer [33]. In another work, the class imbalance problem was solved, and improved detection rate of mitotic nuclei was by using the previously trained CNN model [34]. Yap et al. focused on automated lesion detection in the breast by using a deep-learning approach. The main drawback of this proposed methodology was that it required more time to train a dataset means the problem occurred during the training process [35].

2.1 Strengths and weakness of related work with our proposed study

Many evolving technologies and methods like Computer-aided detection (CAD) systems, Machine learning (ML), Artificial intelligence (AI), Deep learning (DL), transfer learning (TL), etc. [41] have been used and proposed for BC classification in the medical research field. In previous studies, lots of researchers suggested many machine learning (ML) classifiers for the classification of IDC but ML classifiers were not suitable due to the requirement of a large dataset. Deep neural networks and training from scratch were not suitable for the training model because of high computational cost, GPU limitation for large dataset training, Insufficient labeled images in the medical field, and lack of data [22]. In recent studies, Transfer learning has also overcome the data insufficient problems in the medical research field for automated classification of IDC breast cancer histopathology images. However, there are many problems like class imbalance, overfitting, and less accuracy rate during the exposure and classification of carcinoma BC [16]. Deep learning models and hand-constructed feature extraction methods were used to extract the highest suitable set of hybrid features from IDC images. A Kaggle IDC dataset was used for the experiment. Experimental results demonstrated that the combination of manually created features with MobileNet model features improved classification accuracy91 percent, but achieved the lowest F1-score, precision, and recall (87 percent, 88 percent, and 85 percent, respectively)[34]. No doubt, all classification, and detection systems achieved better results for BC using breast histopathology images. But experimental results of existing research studies provided the lowest accuracy rate and f-score value. On the other hand, for the automated classification of invasive ductal carcinoma (IDC) breast cancer, our proposed TransResCNN model achieved better and improved results in comparison with existing research work. The proposed research methodology used a pre-trained ResNet18 CNN model using transfer learning. In comparison to prior research investigations, our proposed methodology effectively achieved an accuracy rate of 90.76% and an F1-score rate of 93.56% using the same dataset of breast histopathology images. In this research field of study, Our main focus is to improve the performance of the classification model and to solve data insufficiency, class imbalance, overfitting, and vanishing gradient problems. The rest of the section explains our methodology to achieve the objective and significant steps to find the solution to problems stated in the literature.

3. Proposed Methodology

There are various existing research studies and enabling techniques for the binary classification of carcinoma BC from breast histopathological images. It is still difficult for a pathologist to classify carcinoma conveniently from histopathological images in less time and accurately. The main objective of our proposed study has to deliver a reliable and accurate solution for IDC classification and also try to overcome the problems in the literature. In this proposed methodology, an efficient methodology has been proposed in which we have defined the classification model as the TransResCNN model. TransResCNN is described as transfer learning applied to the pre-trained residual network (ResNet) CNN model. In our proposed methodology TransResCNN was utilized for the reliable and precise classification of invasive ductal carcinoma (IDC) breast cancer. The implementation of experimental work was performed on google colab by using Python programing language. The important package was NumPy, Pandas, FastAi, and Matplotlib. The transfer learning (TL) technique was used for the best accuracy result. TL provided an automated model to save time, remove errors, and overcome the problems associated with classifying invasive ductal carcinoma which is a well-known category of carcinoma BC. The publicly accessible breast histopathology images dataset has been utilized in this research field of study. The workflow of the proposed methodology is described in Figure 1. The rest of the part of this section explains the steps of our proposed methodology.

3.1 Dataset Description

For the invasive ductal carcinoma (IDC) breast cancer classification task, the Publicly accessible breast histopathology images dataset acquire from the Kaggle database [35]. The dataset consisting of 162 whole mount slide images of BC samples was scanned at a magnification factor of 40x and 277524 image patches having a size of 50x50 were taken out which contained 198738 negatives (-) IDC and 78786 positive (+) IDC patches. Every image patch has a specific file name and format in this dataset. The format of the file name consists of patient ID, X-Coordinate, and Y-Coordinate are coordinates where each patch of images cropped from, respectively. C is the class assigned to each patch where Class 0 indicates Non-IDC and Class 1 indicates IDC. Table 1 lists the breast histopathology images dataset description.

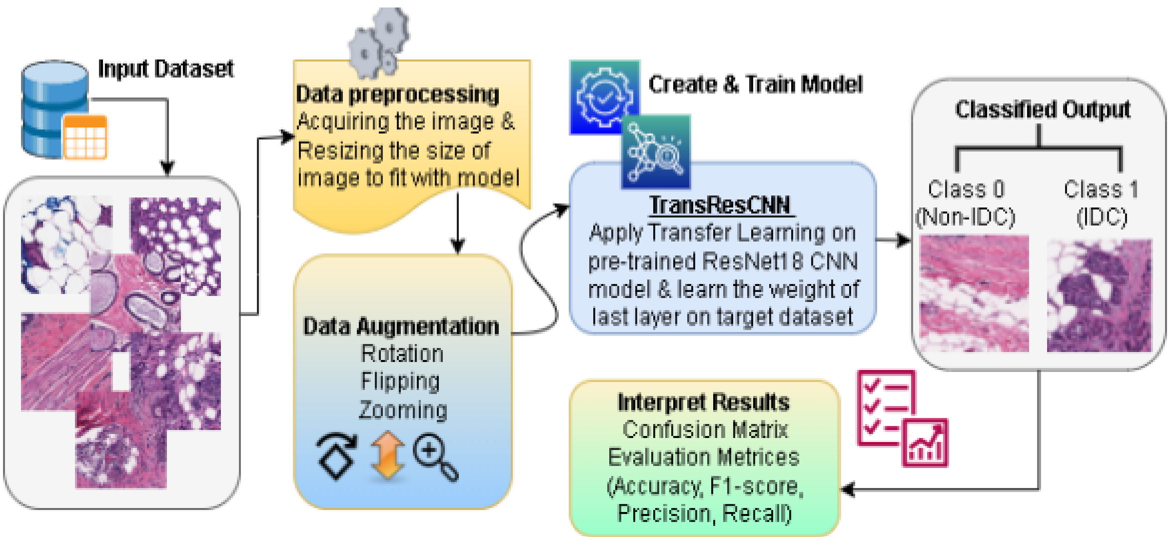

Figure 1. Workflow Diagram of Proposed Methodology

3.2 Data Preprocessing

An essential and significant step before dataset utilization is data preprocessing. In the imaging research field, lots of problems occur due to image-wise assessment. In preprocessing step firstly, we acquired the dataset from the Kaggle database and import all necessary libraries for preprocessing task. Image patches from the breast histopathology images dataset were scanned at 40x and each patch was reshaped at 50 by 50 pixels. The dataset is stored as .jpg files in two different folders belonging to class 0 and class 1. Then import the dataset which is one of the significant steps in preprocessing the data. The data preprocessing task involved resizing the image in such a way it fits with the pre-trained neural network requirement. Each pre-trained model used different sizes of images. We used the pre-trained RestNet18 CNN model in this research work. ResNet18 CNN model required a 224 x 224 size image. So, we have set the size of the image patches to 224 in this case.

Table 1. Dataset Description (Example of a few samples)

File Format	Patient sID	x coordinate	y-coordinate	Class
10254_idx5_x101_y1201_class0.png	10254_idx5	101	1201	0
10253_idx5_x501_y401_class1.png	10253_idx5	501	401	1

3.3 Data augmentation

Data augmentation is an influential technique used to enhance the size of data artificially by applying specific processing to images for making the model more flexible. Common data augmentation techniques were width shift, rotation, flipping, and, zooming [14]. In the proposed methodology, we have applied flipping vertically, zooming, and rotation on the training set. Figure 2 shows the advantages of using data augmentation technique.

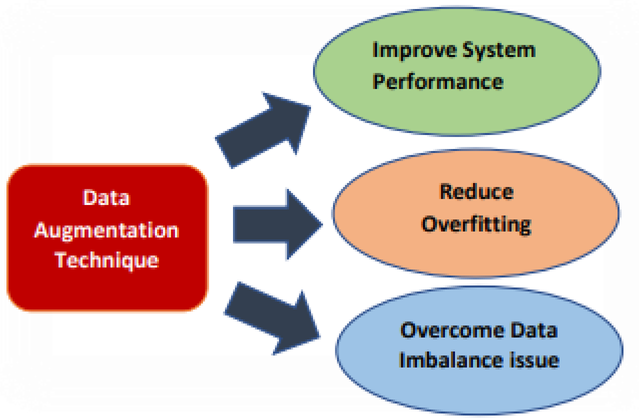

Figure 2. Advantages of using Augmentation Techniques

3.4 Transfer Learning Process

Transfer learning is one of the enhancing technologies in computer vision applications which learned the knowledge from the models trained on millions of images to solve some problem, then transferred this learned knowledge to solve another but similar problem. Fine-tunning, Feature extraction, and pre-trained are various methods of using transfer learning. Typically, the first layers of the model are trained on a large number of dataset images for example ImageNet which contain millions of images. While the last layers of the pre-trained model are trained on another task dataset of related problems. Transfer learning provides faster and more efficient performance by using the best learning rate starting with the right initialization of weights. Figure 3 describes the workflow of the transfer learning approach.

3.5 Classification Model For IDC

The most widely used neural networks or convolutional neural network models played a dynamic role in the medical research field of images[36]. As in our study, we have defined the name of the classification model as TransResCNN. TransResCNN is described as transfer learning applied to the pre-trained residual network (ResNet) CNN model. The proposed methodology used a pre-trained ResNet18 CNN model for the classification of invasive ductal carcinoma (IDC) breast cancer. ResNet stands for Residual Neural Network which is the most prevalent Convolutional Neural Network (CNN) architecture. ResNet consists of residual blocks which are connected in a series with skip connections.

Figure 3. Workflow of the transfer learning process

ResNet has introduced skip or shortcut connections that fit the input of the network from the prior layer to the next layer of the network. In a traditional convolutional layer, convolutional layers are stacked one after the other. While in a residual network with a skip connection, all convolutional layers are stacked one after the other and data travel through the layers but the real input directly adds up to the output of the convolutional block. In this way, many convolutional layers in the model are skipped Figure 4 shows the traditional convolutional layer versus the residual network with a skip connection. In a traditional convolutional layer, convolutional layers are stacked one after the other. While in a residual network with a skip connection, all convolutional layers are stacked one after the other and data travel through the layers but the real input is directly added up to the output of the convolutional block. In this way, many convolutional layers in the model are skipped. Figure 5 shows a basic building block diagram for the residual network in which x is the actual input that has directly added to output f(x) of the convolutional block by skipping all layers. A residual neural network avoids information loss during training and will help the enhancement of model productivity. ResNet protected the model from random fluctuation and make the model less error-prone during the training process.

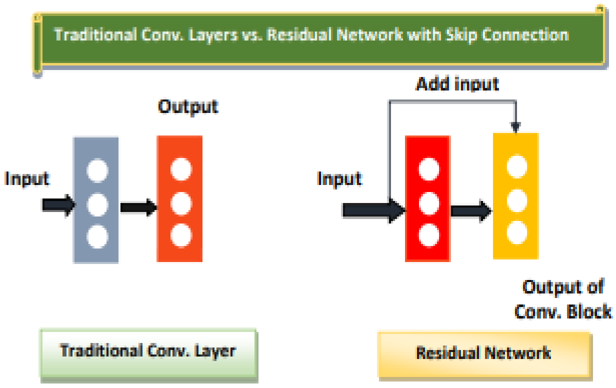

Figure 3. Traditional Conv. Layers VS Residual Network with Skip

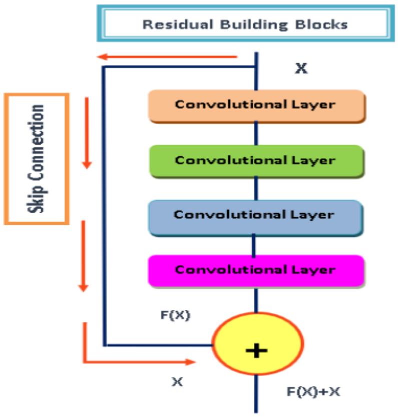

Figure 5. Basic Residual Building Block

3.6 Evaluation of Experimental Results

In this study for performance evaluation, a confusion matrix was used which is one of the excellent tools for binary class classification. Table 2 demonstrates the confusion matrix for binary class classification. Various performance evaluation terms are defined below:-

- True Positive (TP): Actual value is positive and the predicted value is positive.
- False Positive (FP): Actual value is negative but the predicted value is positive.
- True Negative (TN): Actual value is negative and the predicted value is negative.
- False Negative (FN): Actual value is positive but the predicted value is negative.
- Accuracy: It states the correct portion or percentage of a dataset that is properly classified.
- Precision: It states the model's ability to classify positive values precisely.

- Recall: It states the model's capability to determine all positively associated classes in the dataset.
- F1-score: It states the accuracy of the model on the dataset and also defines the weighted average result of two metrics precision and recall.

Table 2. Description of Confusion Matrix

	Class 1 Predicted Value	Class 2 Predicted Value
Class 1 Actual Value	TP	FN
Class 2 Actual Value	FP	TN

4. Results and Discussion

The performance of the proposed TransResCNN model was evaluated by using a confusion matrix and other standard metrics such as classification accuracy, F1-Score, precision, Recall, TPR, FPR, TNR, and FNR.

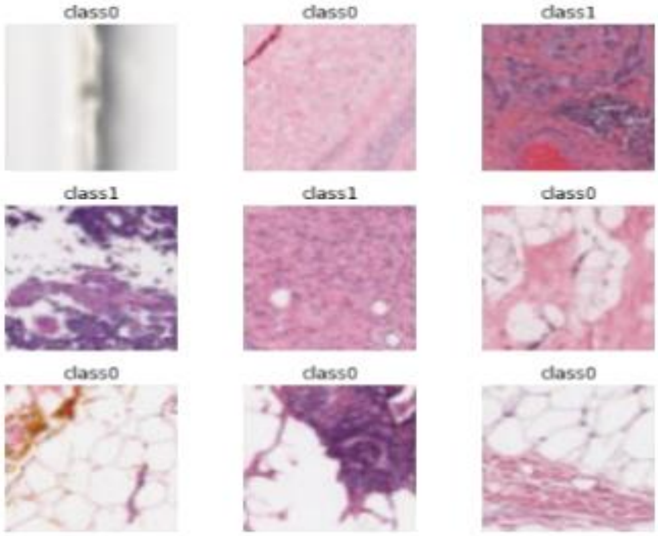

Figure 6. Data Exploration Result

4.1 TransResCNN Results

This section explains the classification results of our proposed methodology TransResCNN. In this proposed work transfer learning was applied on a pre-trained ResNet CNN model using a publicly accessible breast histopathology images dataset As the dataset consisted of 162 whole-mount slide images of BC. 277524 total images were scanned at a magnification factor of 40x. The size of image patches was kept at 224 for ResNet18. A total of 80 percent of the dataset was used for training and 20 percent of the dataset was used for the validation set. The size of the validation dataset was 111,009. A test set can be used but it is kept optional in this case. The overfitting problem has not present during the training of the ResNet18 model. A data augmentation technique was applied which has reduced the overfitting problem and is useful for a large amount of unseen data. A pre-trained ResNet18 model was utilized for the classification of IDC breast cancer from breast histopathology images. The most important benefit of using ResNet is that deep networks were very tough to train because of the vanishing gradient problem. Since, the ResNet model reduced the vanishing gradient problem that occurred during training, makes the training process faster, and preserved the gained knowledge. Data exploration results of image patches including non-IDC (class 0) and IDC (class 1) patches are illustrated in Figure 6. Then we applied transfer learning with a pre-trained model for the classification of IDC. Here, the advantage of applying transfer learning is the convention of a pre-trained model. Since it did not require a large amount of data for the training process. In this way, transfer learning enhanced the system performance and saved training time. After the employment of TL on the pre-trained ResNet18 CNN model, the result of the initial learning rate setting is described in Figure 7. TransResCNN Model was trained to find the learning rate that increases the learning ability of the model by optimization. To control the training process, Hyperparameter tuning was applied to the model. The result in Figure 8 illustrated that the hyperparameter was one of the adjustable parameters which helped to find the best learning rate of the model and provided the significance in the best performance.

4.2 Confusion Matrix

Confusion Matrix used for performance evaluation of invasive ductal carcinoma (IDC) breast cancer classification. Moreover, various performance evaluation metrics are designed for performance evaluation. Figure 9 shows the result of the confusion matrix for the TransResCNN model.

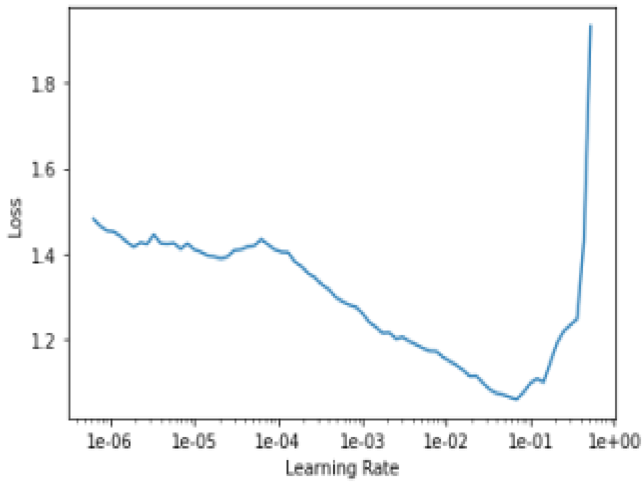

Figure 7. Initial Learning Rate

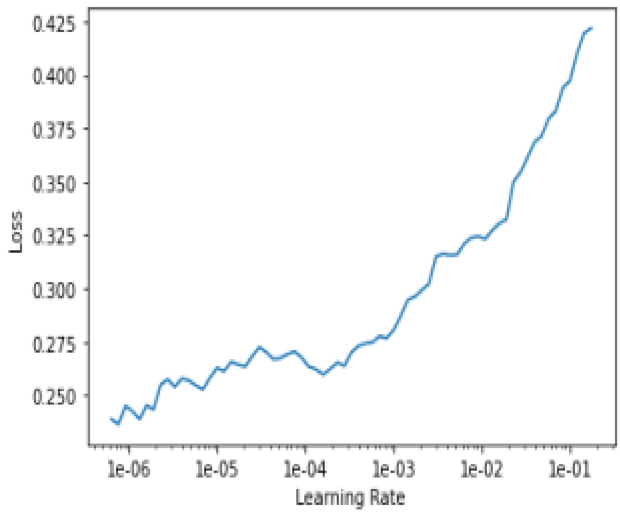

Figure 8. Hyper Parameter Tuning

A total of 111,009 data were used to check the performance of the model. From this, the model classified a total of 1,00,755 patches as truly classified and 10254 patches were false classified. The classified values show that the classification model used in the proposed methodology provided good results.

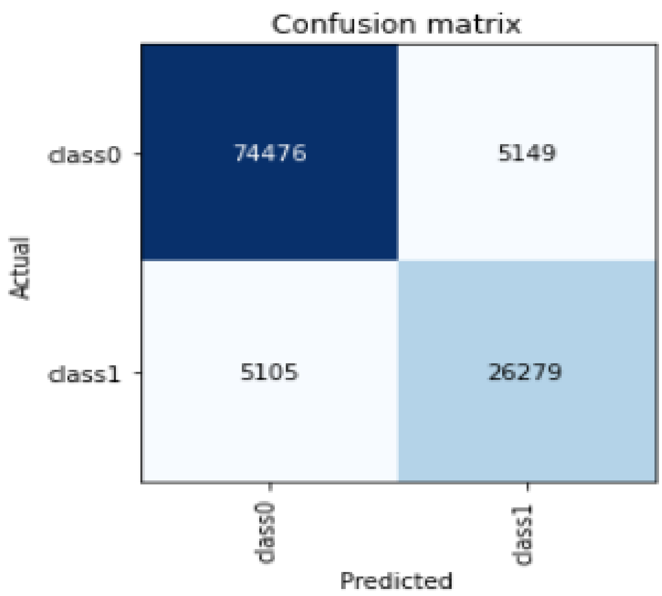

Figure 9 Confusion Matrix for TransResCNN Model

4.3 Evaluation Metrics

In the experimental work of this research study, TransResCNN achieved a better accuracy rate of 90.76% which demonstrates model performed an accurate classification of invasive ductal carcinoma BC. The proposed framework also obtained the best value rate of 93.56% for F1-Score, the Precision value of 93.58%, and the Recall of 93.53% for the classification of IDC breast cancer. The performance measure for evaluation metrics is also described in Table 3 which shows the different quantitative or measurement values in percentage (%) of performance evaluation metrics for Invasive ductal carcinoma (IDC) breast cancer classification in this research work. Also, a graph is illustrated in Figure 10 which demonstrates the performance measurement values of all evaluation metrics in percentage (%). These achievable performance measures will help in the medical field for the timely and accurate classification of breast cancer.

Table 3. Performance Evaluation for IDC Breast Cancer

Evaluation Metrics	Measurement (%)
Accuracy	90.76%
F1 Score	93.56%
Precision	93.58%

4.4 Finding Objectives of the Study

This section explains how the objective of the proposed study was achieved and also the strength of our research study. These findings are the main advantages of our research study.

4.4.1 Overcome the class imbalance problem

As in the literature and discussion section, we have seen that the F1 score has less rate which shows the class imbalance problem was present in existing research work. Data augmentation helped in our methodology to overcome this problem. Also, for resolving this problem the best way is to choose a better evaluation metric. Since to overcome the class imbalance problem from breast histopathology images dataset F1-score metrics are specially intended. In this research study our proposed methodology achieved the highest F1 score of 93.56% rate in comparison with the existing research study. The highest value of the F1-score metric demonstrates that the Proposed TransResCNN model performs better in reducing the class imbalance problem as compared to existing work done in this research field of study.

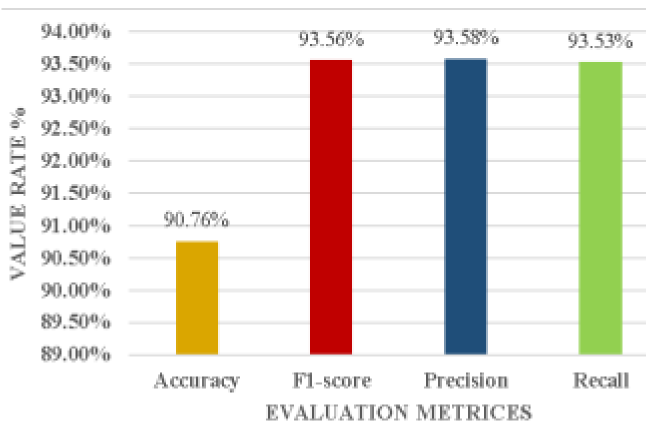

Figure 10 Performance Evaluation Graph of Proposed Methodology

Reduced overfitting with a large medical imaging dataset Overfitting problem occurs when trying to achieve the best fit of our model on training data, whereas on working with unseen and new data the model does not give generalizability. The efficiency of a model increased by enhancing the data when practiced with more data, we have used the data augmentation technique. This is an influential technique that is used to rise the size of data artificially by applying specific processing to images for making the model more flexible and generalizable. Another way used to reduce the overfitting is lowering the capacity of the model by removing the layers or using less no. of layers which has made the model more generalizable and efficient.

4.4.2 Reduced vanishing gradient problem of a model

The random fluctuation of the model causes the vanishing gradient problem. To reduce and evade this problem we have chosen the residual network. ResNet consists of residual blocks connected in a series with skip connections. In a residual network with a skip connection, all convolutional layers are stacked one after the other, and data travel through the layers but the original input is added to the output of the convolutional block. In this way, many convolutional layers are skipped. The most important benefit of using ResNet is that deep networks are very tough to train because of the vanishing gradient problem. Since, the ResNet model reduced the vanishing gradient problem that occurred during training, makes the training process faster, and preserved the gained knowledge. A residual neural network has evaded information loss during training and helped to raise the performance of the model. The skip connections helped the ResNet to protect the model from random fluctuation and make the model less error-prone during the training process.

4.4.3 Improved the accuracy

For the accurate classification of invasive ductal carcinoma (IDC) Breast cancer, the TransResCNN model is proposed. In which the ResNet18 CNN model is used with a transfer learning technique. TransResCNN model achieves the objective of this research work which is to get a higher accuracy rate for the classification of IDC breast cancer. The reason to use a residual network (ResNet) is to enhance the classified efficiency of the model. Because the ResNet model is easy to get optimization when working with higher depth since the model produces less training error. ResNet has introduced skip or shortcut connections that fit the input of the network from the previous layer to the next layer of the network. As has been discussed in the above section that a residual neural network avoids information loss during training and increased the efficiency of the model. ResNet model also reduced the random fluctuation of the model that occurred during training, faster the training time. As in this research field of study, TransResCNN model obtained a better accuracy rate of 90.76%. Improvement in accuracy value illustrates that the proposed methodology has enhanced the accuracy and efficiency of the model for IDC classification in comparison with existing research studies. The following sub-section will discuss the comparison of various existing approaches with the results of the proposed TransResCNN model for the classification of breast cancer in histopathology images.

4.5 Comparative Analysis Using the Same Dataset for Classification of BC

In this section, a comparison of various existing techniques has been discussed using the same breast histopathology images dataset. By using the Deep learning approach, Abdolahi et al. [16] classified invasive ductal carcinoma BC by using a deep convolutional neural network (CNN) model as a baseline model trained from scratch, another approach has also been proposed in this study that used transfer learning with pre-trained VGG-16 CNN model as feature extraction and transfers learning via fine-tuning for the automated classification for IDC breast cancer using breast histopathology images. Using the same dataset baseline model achieved 85.62% accuracy and an F1 score of 83.50%. VGG-16 via feature extraction by using transfer learning study achieved an accuracy measure value of 81% and F1-score of 81%, via fine-tuning model obtained 51% accuracy and 35% F1-score.

Table 4. Comparison of Accuracy and F1Score With Previous Research Approaches (Using Breast Histopathology Images dataset)

Ref.	Year	Technique	Method/ Model	Accuracy	F_1Score
[23]	2019	Enhanced Deep Learning Approach	CNN architecture, Accept-RejectPooling	85.00	85.28
[16]	2020	Transfer learning	Base Line Model	85.62	83.50
[16]	2020	Transfer Learning	VGG-16 via feature extraction	81.00	81.00
[16]	2020	Transfer Learning	VGG-16 with finetuning	51.00	35.00
[29]	2020	CNN-based Deep Learning Approach	Conventional Neural NetworkCNN Classifier	84.93	76.07

[26]	2021	Deep learning	CNN architecture	87.00	87.00
[33]	2021	Deep Learning	DenseNet Model	87.20	88.00
[14]	2021	Transfer Learning	DenseNet121 Model	86.97	87.46
[14]	2021	Transfer Learning	ResNet50	84.19	83.84
[14]	2021	Transfer Learning	VGG16	85.50	85.53
[14]	2021	Transfer Learning	EfficientNetB0	84.88	84.36
[37]	2022	Deep Learning	CNN based model	80-86	94-96
[38]	2022	CNN-based Deep Learning Approach	ConvNet-C	88.7	___
Proposed Study		Transfer learning	Proposed Study TransResCNN	**90.76**	**93.56**

In other research, Romano AM et al. has introduced a new pooling layer called accept reject pooling, with pooling sizes 2 by 2. Their results demonstrate a better accuracy measure of 85% and an F1 score of 85.28% [23]. In another experimental work by Alanazi et al., different layered CNN architecture was used for the automated detection of IDC breast cancer, and their result demonstrated that CNN model 3 achieved an 87% accuracy rate and 87% F-score value [26]. Reza & Ma et al., achieved 85.62% accuracy and 84.78% F-score for an automated classification between cancerous and non-cancerous cells in histopathology images [28]. In another work, Siddiqui et al. used deep learning techniques for the classification of cancerous and non-cancerous IDC tissues in whole slide images (WSI). Their result demonstrates that the CNN classifier detects IDC and non-IDC tissues with an accuracy of 84.93% and an F-score of 76.07%. However, the percentage of F-score value is very low which shows the data imbalance problem is not too much solved in the proposed study [29] and Veta et al. used a densely connected convolutional network and improved the balanced accuracy of their proposed model which 87.2% and F-Score was 88.0% [33]. On the other hand, Seemendra et al. proposed an efficient system for the automated classification of BC. The researcher used a transfer learning approach with various pre-trained CNN models. This study also used VGG, DenseNet, EfficientNet, ResNet, and ModileNet for the accurate detection of Invasive ductal carcinoma (IDC) breast cancer. As compared to the existing research field they also got better accuracy with 86.97% using the pre-trained DenseNet model [14]. A convolutional neural network-based IDC prediction model was proposed. In which a sequential Keras model like conv2D, Maxpooling2D, Dropout, Flatten, and Dense was implemented in the developed deep learning technique. Multiple classifiers, including logistic regression (LR), random forest (RF), k-nearest neighbor (K-NN), support vector machine (SVM), linear SVM, gaussian nave bayesian (GNB), and decision tree, were compared to the proposed model. Following assessments, the suggested CNN-based IDC framework offered predictions that were between 80 and 86 percent accurate, between 92 and 94 percent precise, between 91 and 96 percent recall, and between 94 and 96 percent F1-score [37]. While Gupta et al.[38] proposed DL-based scheme to detect IDC. ConvNet-A, ConvNet-B, and ConvNet-C are three separate CNN models that were created entirely from scratch under the proposed method. Additionally, the effectiveness has been verified using the support vector machine (SVM), Knearest neighbor (KNN), random forest (RF), and logistic regression models. With ConvNet-C, they achieved the greatest sensitivity and accuracy of 92.6 percent and 88.7 percent, respectively. In another study, an enhanced DL approach was used to propose the CNN-based model called as CancerNet. A benchmark IDC dataset was used for experimental work. Their suggested model achieved accuracy, Area Under Curve (AUC), precision, recall, and F1-score of 86, 92, 81, 84, and 83 percent, respectively [39]. A different work [40] suggested a deep CNN-based approach for detecting breast cancer. This study evaluates the performance of the pre-trained CNN models EfficientNetB0, ResNet50, and Xception.

On a portion of the IDC dataset, the suggested model with enhanced pre-trained Xception CNN is tuned and evaluated. The IDC dataset attained an accuracy of 88.08 percent. However, all classification and detection systems achieved better results for IDC BC using breast histopathology images. But experimental results of existing research studies gave the lowest accuracy rate and f-score value. On the other hand, for the automated classification of invasive ductal carcinoma (IDC) breast cancer, our proposed TransResCNN model achieved better and improved results in comparison with existing research studies. The proposed research methodology used a pre-trained ResNet18 CNN model using transfer learning. By using the same breast histopathology images dataset proposed methodology attained an accuracy rate of 90.76% and an F1-score rate of 93.56% with the best improvement in percentage in contrast to other research studies. TransResCNN result is compared with various existing research studies using the same breast histopathology images dataset for classification of BC and is evaluated in terms of accuracy and F1-Score. The Numerical results of existing approaches are compared with the proposed TransResCNN model in Table 4. We hope that our proposed methodology will help the pathologist in the medical research field to classify IDC breast cancer in less time with the highest accuracy.

5. Conclusion

In this study, efficient and accurate classification of invasive ductal carcinoma (IDC) breast cancer was performed using the transfer learning technique with breast histopathological images. For this purpose, an effective methodology was proposed in which we have defined the classification model as TransResCNN. TransResCNN was described as transfer learning applied to the pre-trained Residual Network (ResNet) CNN model used for the classification of IDC. For experimental work, a publicly accessible breast histopathological images dataset was used. To inevitably extract the features of images for IDC classification, an efficient pre-trained Residual convolutional neural network, ResNet18 was applied. ResNet model reduced the vanishing gradient problem and also avoided information loss during training, and helped to boost the performance of the model. However, various evolving techniques like augmentation and TL were also applied in this investigated study. Data augmentation has reduced the overfitting and class imbalance problems that will be helpful for a pathologist with a large and unseen dataset. Transfer learning has enhanced the system performance and saved training time. Moreover, for the performance evaluation, the classification model evaluates through a confusion matrix. Several evaluation metrics are also applied like accuracy, precision, F1-score, and Recall. Furthermore, a well-organized comparison of various existing studies with the results of the proposed study has been provided. This study illustrates that our proposed methodology achieved the highest accuracy of 90.76% and an F1 score of 93.56% than previous research studies. In the future, it will be more interesting to extend this study to the patient level to check the performance of the proposed research study. Besides this, we will also try to use the more enhanced deep neural model with transfer learning technique to achieve more highest accuracy on the breast histopathological images dataset. Moreover, the proposed methodology will also be applied to a more challenging dataset in the research field of breast cancer. We hope that our proposed methodology will help the pathologist in the medical research field to classify IDC from histopathology images in less time with the highest accuracy.

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