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EVALUATING THE FEASIBILITY OF THERMOGRAPHIC IMAGES FOR PREDICTING BREAST TUMOR STAGE USING DCNN

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Abstract. *Early-stage and advanced breast cancer represent distinct disease processes. Thus, identifying the stage of tumor is a crucial procedure for optimizing treatment efficiency. Breast thermography has demonstrated significant advancements in non-invasive tumor detection. However, the accurate determination of tumor stage based on temperature distribution represents a challenging task, primarily due to the scarcity of thermal images labeled with the stage of tumor. This work proposes a transfer learning approach based on Deep Convolutional Neural Network (DCNN) with thermal images for predicting breast tumor stage. Various tumor stage scenarios including early and advanced tumors are embedded in a 3D breast model using the Finite Element Method (FEM) available on COMSOL Multiphysics software. This allows the generation of the thermal image dataset for training the DCNN model. A detailed investigation of the hyperparameters tuning process has been conducted to select the optimal predictive model. Thus, various evaluation metrics, including accuracy, sensitivity, and specificity, are computed using the confusion matrix. The results demonstrate the DCNN model's ability to accurately predict breast tumor stage from thermographic images, with an accuracy of 98.2%, a sensitivity of 98.8%, and a specificity of 97.7%. This study indicates the promising potential of thermographic images in enhancing deep learning algorithms for the non-invasive prediction of breast tumor stage.*

Keywords: image analysis, classification, tumor prediction, transfer learning, thermography

OCENA WYDAJNOŚCI OBRAZÓW TERMOGRAFICZNYCH DO PRZEWIDYWANIA STOPNIA GUZA PIERSI PRZY UŻYCIU DCNN

Streszczenie. *Wczesny i zaawansowany rak piersi stanowią odrębne procesy chorobowe. Dlatego też identyfikacja stadium nowotworu jest kluczową procedurą dla optymalizacji skuteczności leczenia. Termografia piersi wykazała znaczny postęp w nieinwazyjnym wykrywaniu nowotworów. Jednak dokładne określenie stopnia zaawansowania nowotworu na podstawie rozkładu temperatury stanowi trudne zadanie, głównie ze względu na niedobór obrazów termicznych oznaczonych stopniem zaawansowania nowotworu. W niniejszej pracy zaproponowano podejście uczenia transferowego oparte na głębokiej konwolucyjnej sieci neuronowej (DCNN) z obrazami termicznymi do przewidywania stadium guza piersi. Różne scenariusze stadium nowotworu, w tym guzy wczesne i zaawansowane, są osadzone w trójwymiarowym modelu piersi przy użyciu metody elementów skończonych (MES) dostępnej w oprogramowaniu COMSOL Multiphysics. Pozwala to na wygenerowanie zestawu danych obrazów termicznych do trenowania modelu DCNN. Przeprowadzono szczegółowe badanie procesu dostrajania hiperparametrów w celu wybrania optymalnego modelu predykcyjnego. W związku z tym różne wskaźniki oceny, w tym dokładność, czułość i swoistość, są obliczane przy użyciu macierzy pomyłek. Wyniki pokazują zdolność modelu DCNN do dokładnego przewidywania stadium guza piersi na podstawie obrazów termograficznych, z dokładnością 98,2%, czułością 98,8% i swoistością 97,7%. Badanie to wskazuje na obiecujący potencjał obrazów termograficznych w ulepszaniu algorytmów głębokiego uczenia się w celu nieinwazyjnego przewidywania stadium guza piersi.*

Słowa kluczowe: analiza obrazu, klasyfikacja, przewidywanie nowotworów, uczenie transferowe, termografia

Introduction

The Breast cancer is a chronic and common disease that often affects women worldwide. In 2020, the World Health Organization (WHO) reported 685,000 deaths and 2.3 million new cases related to breast cancer [3]. Several factors, including age, genetics, hormonal imbalances, and environmental exposures, can contribute to breast cancer [10]. Early-stage cancer primarily exhibits localized growth without dissemination, while advanced-stage cancer is characterized by the spread of the disease [7]. The disease's progression from early to advanced stages can lead to more aggressive treatments and poorer outcomes. For this reason, the accurate determination of breast cancer stage, typically based on tumor size, is essential for choosing the most appropriate treatment, and improving the patient's outcomes [1].

Traditional methods, such as biopsy, ultrasound, and mammography, have long been employed for this purpose. The objective of a biopsy is to identify the type and stage of the tumor and evaluate its potential invasiveness. This procedure is conducted by a medical professional, such as a surgeon, who carefully selects the site for tissue collection, often guided by imaging techniques like ultrasound or CT scans [2]. Once the sample is obtained, it is then subjected to laboratory analysis, including histological examination and molecular testing. Potential risks associated with biopsies include moderate pain, post-procedural bleeding, and risk of infection at the biopsy site.

Mammography is a widely used breast cancer screening tool, utilizing X-rays to create detailed breast tissue images through differential X-ray attenuation. The procedure involves breast compression between plates to reduce scatter and ensure consistent thickness, with resulting images analyzed by radiologists for breast tumor stage detection [14]. However, mammography has limitations such as reduced sensitivity in dense breast tissue, ionizing radiation exposure, and patient discomfort due to breast compression [18]. These challenges underscore the need for non-invasive screening alternatives for improved breast cancer staging.

Breast thermography is a promising method for early breast cancer detection, characterized by its non-invasive nature, absence of radiation exposure, and cost-effectiveness [9]. It relies on the concept that cancerous cells exhibit higher metabolic activity, generating more heat than normal cells [11]. Thermography offers a non-invasive and radiation-free approach to detect the existence of potential tumors, contrasting with the radiation exposure of mammography and the operator dependency of ultrasound, enhancing patient comfort and safety. However, the determination of the stage of a breast tumor based on thermography is a critical challenge due to the scarcity of thermographic images with labeled tumor stages. Addressing this issue is crucial for enhancing the artificial intelligence algorithms to predict tumor stage by thermal imaging. Advanced simulation methods offer a promising solution to overcome this limitation [12].

In this study we developed a comprehensive approach to predict the stage of breast tumors based on thermal image dataset. Our key contributions could be summarized as follows:

- We developed a well-labeled thermal images dataset including several scenarios of early and advanced-stage breast tumors using FEM. That allows an understanding of thermal patterns obtained from various scenarios of breast cancer.
- We proposed a pre-trained model (MobileNet) for predicting tumor stage based on thermal images. This provides a good compromise between better prediction performance and computational efficiency.

- We selected the optimal predictive model through a detailed investigation of the hyperparameters tuning process. This contributes to improved generalization for the proposed DCNN model to perform well on unseen data.

The rest of this paper is structured as follows. Section 1 details our methodology from the data generation process to the formulation of the DCNN model. In section 2, we discuss the obtained results during the hyperparameters tuning process to select the optimal model. In section 3, we present the concluding remarks of the entire study.

1. Methodology

The methodology includes several key phases: Data generation process using FEM, data preparation involving labeling and splitting, and the development of the DCNN model.

1.1. FEM-based breast tissue modeling

First, we designed a hemispherical model (Figure 1) for simulating the breast geometry including tissues such as skin, gland, fat, and muscle in the COMSOL software. Then, we applied the Pennes equation (1) [5] for simulating and studying thermal distribution in breast tissues for different tumor scenarios. Table 1 summarizes the thermal properties considered in the modeling [16].

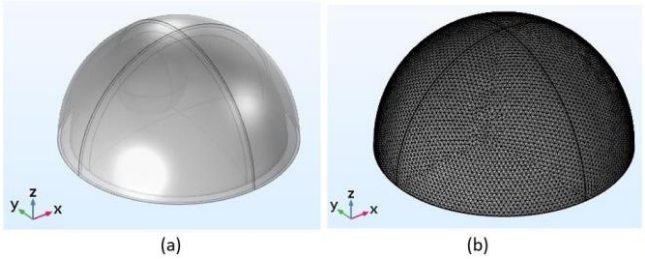

Fig. 1. (a) Breast geometry in 3D modeling. (b) Generated mesh

$$\nabla(k_i \cdot \nabla T_i) + c_b \cdot \rho_b \cdot \omega_{b,i}(T_b - T_i) + q_{m,i} = 0 \quad (1)$$

where i represents the breast layers. The thickness of skin, fat, gland, and muscle is set to 1.6 mm, 5 mm, 43.4 mm, and 15 mm respectively. T_i, and $q_{m,i}$ is respectively the temperature and the metabolic heat generation rate of the tissues. T_b is the arterial blood temperature (37°C), k_i is the thermal conductivity for each tissue, $\omega_{b,i}$ is the blood perfusion rate for each tissue. A room temperature of 25°C is set into the model, which reflects the common range for medical room temperatures.

Table 1. Thermal characteristics of breast tissue

	q_m (W/m^3)	k (W/m.K)	ω_b (ml.s^{-1}.ml^{-1})
Skin	368.1	0.45	0.00018
Fat	400	0.21	0.00022
Gland	700	0.48	0.00054
Muscle	700	0.48	0.00270
Tumor	70,000	0.62	0.01600

1.2. Data collection

Researchers categorized cancer into early and advanced-stage tumors (table 2) [6]. The first tumor category (T1-stage) consists of tumor sizes less than 20 mm. This early-stage category require less aggressive treatment in many cases. The second category (T2-stage) includes tumors between 20 mm and 50 mm. This last may require more aggressive treatments, including high-dose of chemotherapy and radiotherapy. The other categories contain tumors larger than 50 mm, which represent tumor metastases that are very difficult to treat.

Table 2. Range of tumor stage T1 and T2

Tumor stage	T1	T2
Range of tumor size (mm)	2 - 20	21 - 40
Image data	590	569
Dissemination risk	Low	High

In this study, we will focus on predicting T1 and T2 tumor stage categories, which can improve the prognosis and the chances of recovery. Using FEM modeling previously described in section 1.1, we include various permutations of tumor sizes and locations resulting in a dataset of 1159 different cases of thermographic images. Each image has a resolution of 224×224 pixels as shown in figure 2.

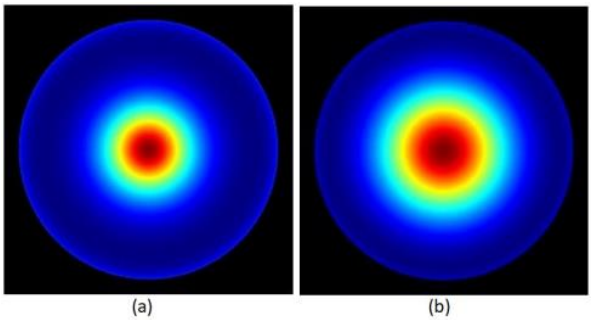

Fig. 2. Example of thermal images generated: (a) T1-stage tumor. (b) T2-stage tumor

The early-stage class contained 590 images, while the advanced-stage class contained the remaining 569 images. The dataset was labled and randomly split into training and validation sets with a ratio of 85:15, with 984 images used for training and 175 images for test. The training set was used to train our DCNN model, while the test set was used to evaluate the model's performance.

1.3. Architecture of the pre-trained DCNN model

Our proposal involved the use of CNN-based MobileNet architecture available on Teachable Machine 2.0, which is a web-based tool that uses Google Cloud services to simplify and accelerate the creation of machine learning models for image classification. MobileNet uses depthwise separable convolutions (DSC) [17] that reduce the number of parameters and computations required while maintaining accuracy [13]. Figure 3 shows the MobileNet principle.

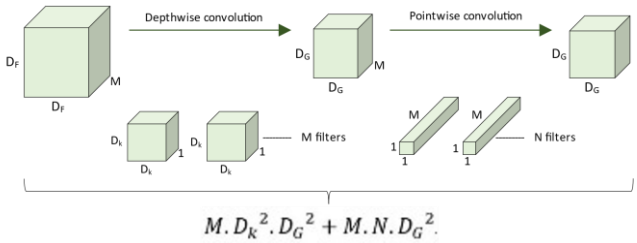

Fig. 3. Depthwise separable convolution principle

In depth wise convolution, one filter is applied to each input channel independently with fewer parameters. Then, in pointwise convolution, 1×1 filters are applied to combine the output feature maps for dimensionality reduction. The mathematical expression of depthwise and pointwise convolution is formulated in (2) and (3). Finally, we get (4) [19].

$$D_{x,y,m} = \sum_m \sum_{i,j} K_{i,j,m} \cdot I_{x+i-1,y+j-1,m} \quad (2)$$

$$P_{x,y,m} = \sum_m K'_{m,n} \cdot D_{x,y,m} \quad (3)$$

$$P_{x,y,m} = \sum_m \sum_{i,j} K'_{m,n} \cdot K_{i,j,m} \cdot I_{x+i-1,y+j-1,m} \quad (4)$$

where, $D_{x,y,m}$ is output of depthwise convolution, $P_{x,y,m}$ is output of pointwise convolution, I is input image, K is depth wise convolution kernel, K' is pointwise convolution kernel.

Figure 4 represents the global architecture adopted on Teachable Machine 2.0 for tumor stage detection. The model's architecture is composed of multiple layers of DSC with rectified linear activation function (ReLU) (5) [15], followed by global average pooling, a fully connected layer, and a softmax activation function (6) [20] for the classification of images. We developed the initial dense layer and the last softmax layer with two classes (T1-stage and T2-stage thermal images). The model learns to extract features in a more efficient way by separately applying filters to each channel of the input, rather than convolving the entire input with a single filter. This reduces the number of computations needed in the convolutional layer, making the model faster and more memory-efficient, while still preserving important features in the data [8].

$$ReLU(z) = \begin{cases} 0 \; if \; z < 0 \\ z \; if \; z \geq 0 \end{cases} \quad (5)$$

$$softmax(z)_{[i]} = \frac{e^{z[i]}}{\sum_j e^{z[j]}} \quad (6)$$

where, z is the input.

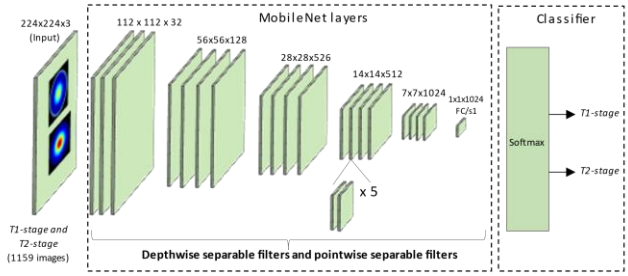

Fig. 4. Architecture adopted for tumor stage prediction

1.4. Hyperparameters tuning process

Hyperparameter tuning is a crucial step in the development of an accurate deep learning models [4]. Figure 5 indicates the process followed for selecting the best parameter combination. As shown in the flowchart (Figure 5), we considered independ-ent elements for evaluation, which included several combina-tions of epochs (Ep) and learning rates (LR). These elements were chosen to evaluate the test accuracy and loss of the model. By systematically varying these hyperparameters at 16 batch size, we achieved the optimal model able to detect accurately the tumor stage based on thermal images.

2. Results and discussion

We trained our deep learning model using different combinations of learning rates and epochs to investigate their impact on the performance of the model. Especially, we considered three different learning rates (0.00001, 0.0001, and 0.001), and nine different epoch numbers from 20 to 100 with an increment step of 10 for each combination. Figure 6 shows all the obtained combinations of training and test loss curves. As shown in Figure 6, increasing the learning rate up to 0.001 caused large fluctuations and noise on the loss curves. However, when the learning rate decreases to 0.0001 and 0.00001, the training and testing loss curves become smooth with faster convergence to the global minimum. We notice that the loss curves confronted a significant impact by adjusting the learning rate. Thus, tuning the epoch numbers leads to achieving the optimal performance of the model. Figure 7 includes the representation of the confusion matrix obtained from the testing set of each LR and epoch combination. We reported the overall test accuracy in table 3.

From table 3, we notice that the test accuracy is considerably influenced by both the LR and the number of epochs. Thus, the higher accuracy is obtained by running more epochs. Especially, on 80 epochs for the LR (= 0.0001), the model achieved the best performance with an accuracy of 98.28%.

Table 3. Comparative analysis for DCNN model selection

Epoch	Learning rate		
	0.00001	0.0001	0.001
20	86.28%	94.85%	89.14%
30	92%	94.85%	94.28%
40	92%	97.14%	93.71%
50	91.42%	97.71%	96.57%
60	89.71%	92.57%	93.71%
70	94.85%	95.42%	91.42%
80	93.71%	**98.28%**	97.14%
90	92%	97.14%	96%
100	93.71%	95.42%	96%

We summarized the performance metrics for this model in table 4. The table includes six metrics: accuracy, positive predictive value (PPV), negative predictive value (NPV), sensitivity (recall), specificity, and F1-score. Our results show that the model with the LR (= 0.0001) and 80 epochs achieved an accuracy of 98.2%, a sensitivity of 98.8%, a specificity of 97.7%, and an F1-score of 98.7% on the test set, indicating strong performance for tumor staging.

Table 4. Performance results for the optimal model (TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative, n: numerical application)

Parameter	Formula	n	Value
Accuracy	(TP+TN)/Total	(87+85)/175	0.982
Sensitivity (Recall)	TP/(TP+FN)	87/(87+1)	0.988
Specificity	TN/(TN+FP)	85/(85+2)	0.977
PPV	TP/(TP+FP)	87/(87+2)	0.977
NPV	TN/(TN+FN)	85/(85+1)	0.988
F1-score	2*(PPV*Recall)/ (PPV+Recall)	2*(0.977*0.988)/ (0.997+0.998)	0.987

Overall, our results suggest that careful tuning of the hyperparameters contributes for achieving optimal performance with a good fit. Thus, a learning rate of 0.0001 with 80 epochs was proved the optimal combination for our task.

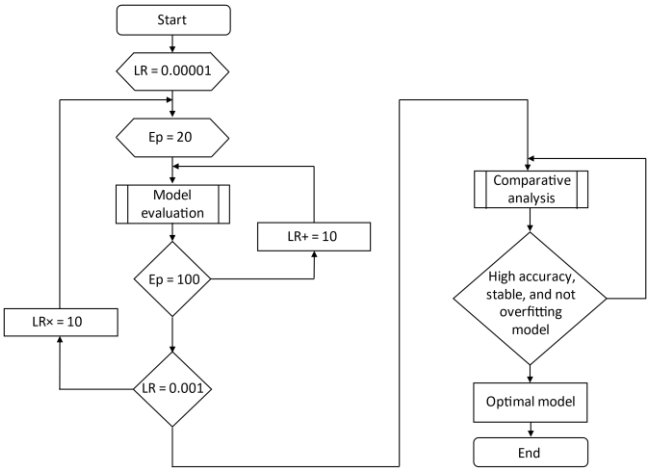

Fig. 5. Flowchart of the hyperparameters tuning process (LR: learning rate, Ep:number of epoch)

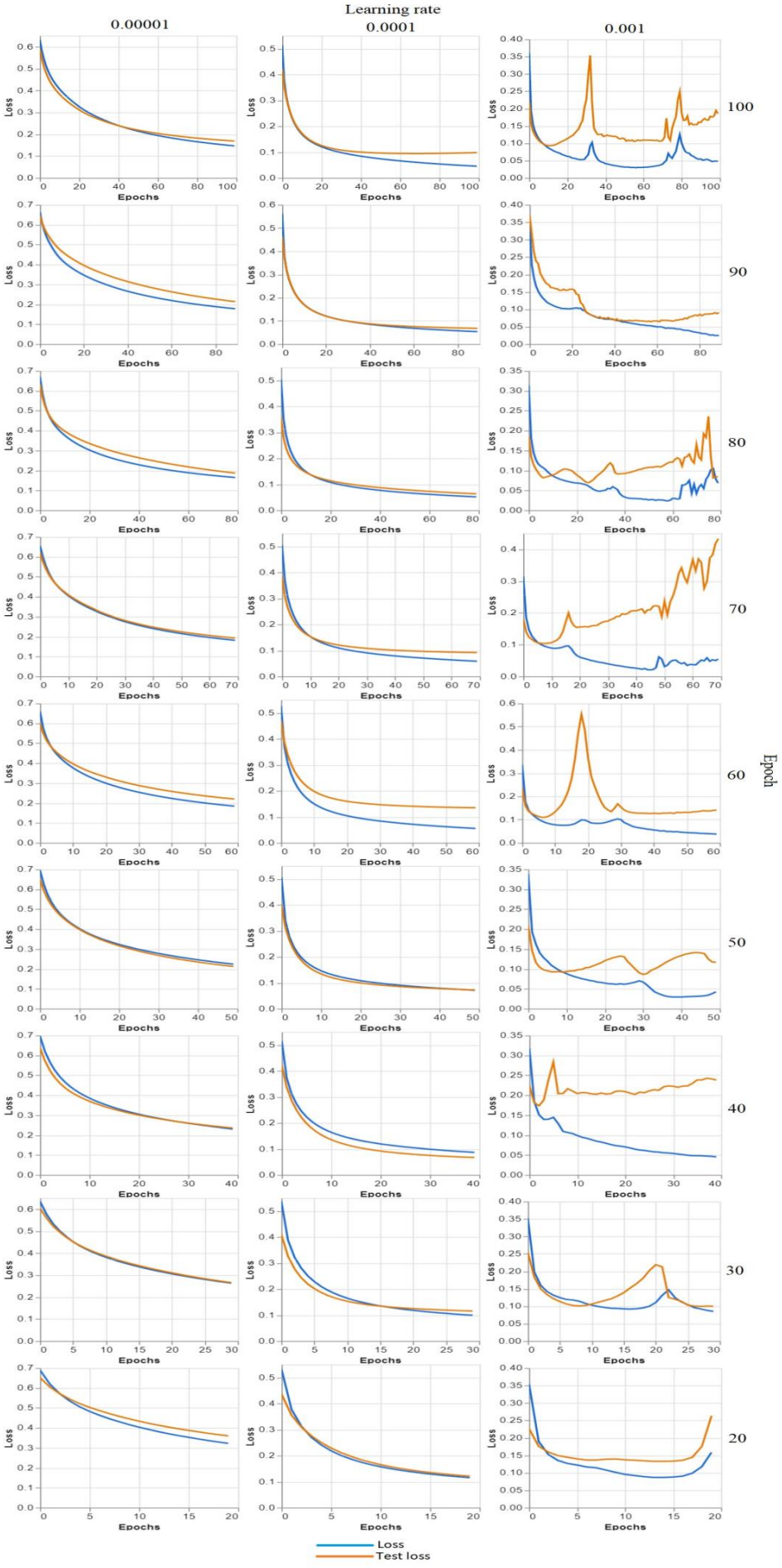

Fig. 6. Loss curves for the proposed model depending on different learning rates (horizontal) and number of epochs (vertical)

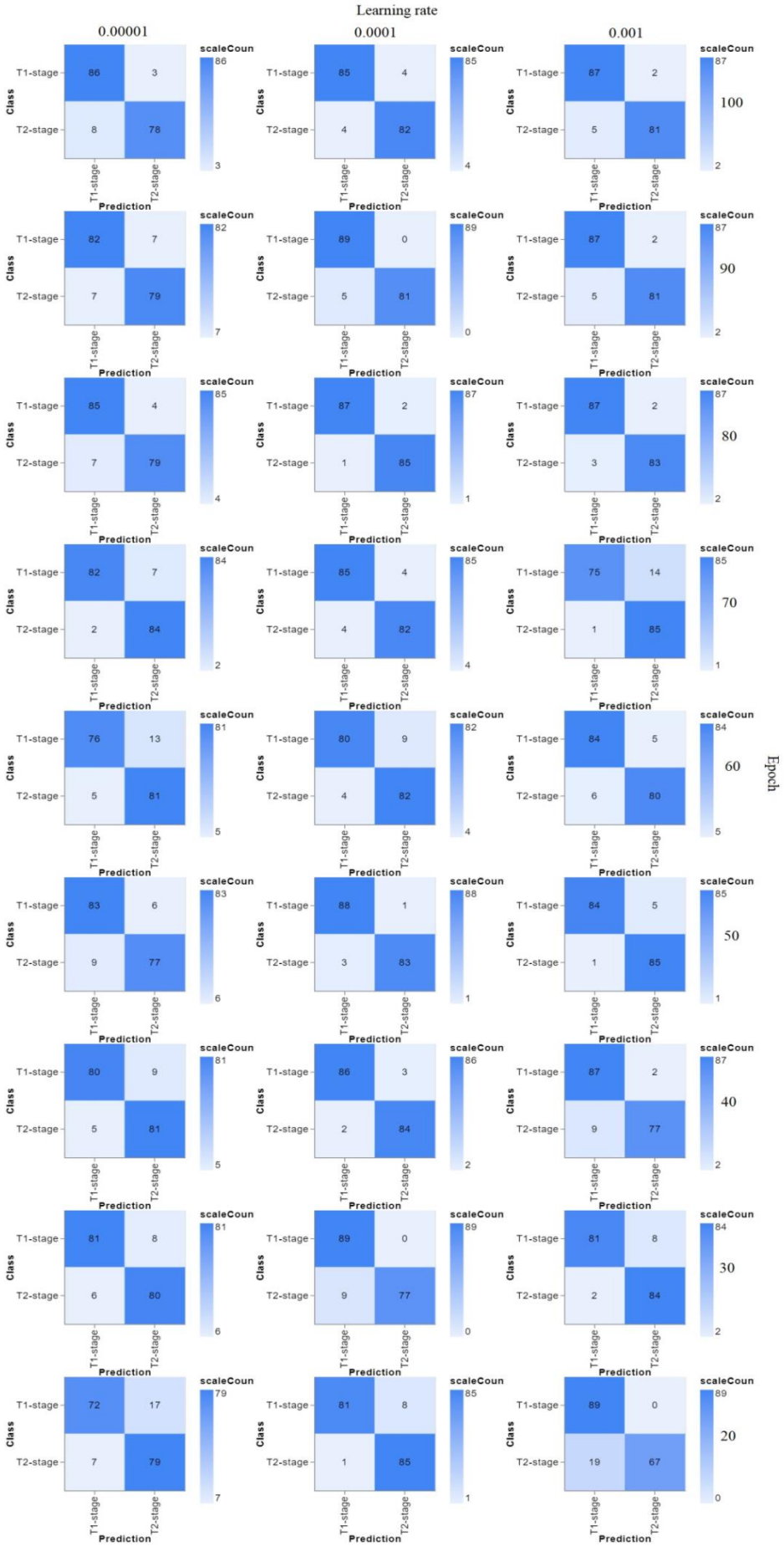

Fig. 7. The evaluation of the confusion matrix for the proposed model on different epochs (vertical) and learning rates (horizontal). The x-axis represents the model's predictions, while the y-axis represents the actual class of the dataset

3. Conclusion

In this paper, we introduced an appropriate DCNN-based methodology to enhance the prediction of breast tumor stage using thermographic images. Using the COMSOL software, we first developed a 3D breast model incorporating skin, fat, mammary gland, and muscle. Then, we included diverse scenarios of early and advanced tumor stages (T1-stage and T2-stage) to generate the thermal image dataset. Each image was labeled according to the corresponding tumor stage category for training the DCNN model. Multiple combinations of learning rates and number of epochs are investigated for adopting the optimal predictive model. According to the results, our approach shows the potential of the proposed DCNN model to predict tumor stage based on thermographic images with a reasonable accuracy of 98.2%. The optimum predictive model is obtained by running more epochs (80) in the LR of 0.0001. This study provides insights into the promising feasibility of thermographic images in combination with transfer learning techniques for tumor stage prediction. In future works, we aim to include the proposed framework in a smart thermographic system for investigating decisions on realistic subjects.

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