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Research Article

Design and Development of an GUI for Pre-Trained Network-Based Automated Classification of Cervical Cancer Cells

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Abstract

Cervical cancer is the second most common cancer in women after breast cancer, causing the death of one woman every two minutes in the world. The most important risk factor originating from the cervix is infection with the papilloma virus (HPV). Cervical cancer screening programs are extremely important to reduce the incidence and death rates of this cancer. The primary goal of screening for cervical cancer is the accurate detection and timely treatment of intraepithelial precursor lesions of the cervix, in order to prevent cervical cancer. With the PAP smear test, cells in the cancerous stage are detected in the endocervical canal, and cancer development can be prevented before the cells turn into cancer with cancer treatment at this stage. The PAP test, which is used in early diagnosis, is an easy-to-apply, low-cost, harmless, high-sensitivity test that also reduces the burden of treatment. Recent developments in the field of artificial intelligence have achieved serious success in the diagnosis of cervical cancer. In this study, a transfer learning-based cervical cancer detection method and an application developed to easily perform these procedures are presented. Cancerous and non-cancerous cervical cells were classified using pre-trained networks. Five popular pre-trained networks, namely Xception, VGG-16, DenseNet, InceptionV3, and InceptionResNetV2, were used for the problem and the obtained performance results were compared. In addition, an application has been developed so that experts working in this field can easily make such classifications. With this application, users can create their own models by conducting a new training, use the model created in this study, and quickly test which class the newly obtained images belong to. As a result of the study, DenseNet network obtained the highest accuracy with 94.72% accuracy. Experimental results show that the proposed approach can provide an inexpensive and rapid decision support system for cervical cancer detection that anyone can apply.

Keywords: Cervical Cancer Cells, Classification, Deep Learning.

Serviks Kanser Hücrelerinin Ön-Eğitimli Ağ Temelli Otomatik Sınıflandırılması İçin Bir Ara Yüz Tasarımı ve Geliştirilmesi

Öz

Serviks (rahim ağzı) kanseri, dünyada her iki dakikada bir kadının ölümüne neden olan ve kadınlarda meme kanserinden sonra en sık görülen ikinci kanserdir. Rahim ağzından kaynaklanan en önemli risk faktörü papilloma virüsü (HPV) ile oluşan enfeksiyondur. Servikal kanser tarama programları, bu kanserin görülme sıklığını ve ölüm oranlarını azaltmak için son derece önemlidir. Serviks kanseri için yapılan taramaların birincil hedefi, servikal kanseri önleme amacıyla, serviksin intraepitelyal prekürsör lezyonlarının doğru tespit edilmesi ve tedavisinin zamanında yapılmasıdır. PAP smear testi ile kanseröz dönemdeki hücreler endoservikal kanalda saptanmakta ve bu aşamadaki kanser tedavisi ile hücreler kansere dönüşmeden kanser gelişimi önlenebilmektedir. Erken tanıda kullanılan PAP testi kolay uygulanabilen, maliyeti düşük, zarar vermeyen, duyarlılığı yüksek ayrıca tedavi yükünü azaltan bir testtir. Son zamanlarda yapay zekâ alanındaki gelişmeler, serviks kanserinin teşhisinde ciddi başarılar elde edilmektedir. Yapılan bu çalışmada, transfer öğrenme tabanlı serviks kanser tespit yöntemi ve bu işlemlerin kolayca yapılabilmesi amacıyla geliştirilen bir uygulama sunulmaktadır. Kanserli ve kanserli olmayan servikal hücreler, ön-eğitimli ağlar kullanılarak sınıflandırılmıştır. Problem için Xception, VGG-16, DenseNet,

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İnceptionV3 ve InceptionResNetV2 olmak üzere beş popüler ön eğitilmiş ağ kullanılmış ve elde edilen performans sonuçları karşılaştırılmıştır. Ayrıca bu alanda çalışan uzmanların bu tip sınıflandırmaları kolay yapabilmeleri amacıyla bir uygulama geliştirilmiştir. Bu uygulama ile yeni bir eğitim yapılarak kullanıcılar kendi modellerini oluşturabilir, bu çalışmada oluşturulan modeli kullanabilir ve yeni elde edilen görüntülerin hangi sınıfa ait olduklarını hızlı bir şekilde test edebilmektedirler. Çalışma sonucunda, DenseNet ağı %94,72 doğruluk ile en yüksek doğruluk elde edilmiştir. Deneysel sonuçlar, önerilen yaklaşımın rahim ağzı kanseri tespiti için herkesin uygulayabileceği ucuz ve hızlı bir karar destek sistemi sağlayabileceği gösterilmektedir.

Anahtar Kelimeler: Serviks Kanser Hücreleri, Sınıflandırma, Derin Öğrenme.

1. Introduction

While some cells use their ability to divide for regeneration and repair of injured tissues, cancer cells lose this consciousness and divide uncontrollably [1]. Although there are many types of cancer, they all start with the uncontrolled proliferation of abnormal cells [2]. According to the World Cancer Report, 14 million new cancer cases and 8.2 million cancer-related deaths were reported worldwide in 2012 [3].

It constitutes 3.6% of female cancers in developed countries and 15% in underdeveloped countries [4]. Although it is most common between the ages of 50 and 59, 65% of invasive cervical cancers are seen in the age group of 40-60 years in our country. Cervical cancer is the fourth most common malignancy in the world and can be considered a major global health problem [5]. It occurs in approximately 500,000 women worldwide each year. A large proportion of this number is in less developed countries where effective screening systems are not available [6]. In 2005, 260,000 women died from this disease in the world, and approximately 95% of these deaths occurred in developing countries. While the expected 5-year survival rate in patients is 66% in developed countries, it is below 50% in developing countries [7]. According to a study in Turkey in 2005, cervical cancer (5.31%) ranks 10th among the 10 most common diseases in women [8]. Risk factors that cause cancer include exposure to papillomavirus (HPV), smoking, and immune system dysfunction [6]. Early diagnosis is key to preventing death [7]. Cervical cancer screening in Turkey is performed by HPV DNA or pap-smear test applied every 5 years to women aged 30-65. Women with a normal Pap-smear test result or a negative HPV DNA test result are called for repeat screening after 5 years [8]. In Turkey, efforts are being made to develop cervical cancer screening programs with various methods such as PAP (Papanicolau) smear and HPV DNA screening and to spread the screenings to the general population. Educated health professionals have important duties in determining cervical cancer risk factors and providing education and counseling to individuals regarding risk factors. In the prevention of cervical cancer, especially health personnel working in primary health care services should take an active role in increasing the level of awareness of women in the society they serve and directing them to early diagnosis. With an approach that includes prevention, effective screening, early diagnosis and treatment programs, the high mortality rate due to cervical cancer can be reduced. Early and effective screening helps detect precancerous changes that can turn into cancer.

Since the Pap-smear test requires specialist technicians, doctors and special medical equipment, and most of them are not available in many developing countries, the disease cannot be diagnosed early and mortality rates are high. In addition, since the manual cell interpretation process is tiring and long, extensive research has been carried out on the use of computer-based machine learning [9].

Zhang et al. [10] used the CNN algorithm in their study in 2017. Deep learning and transfer learning methods were used for the first time in cervical cell classification. Herlev had a success rate of 98.3% in Pap Smear and HEMLBC datasets. Sompawong et al. [9] conducted similar studies on cervical cancer and used the Mask R-CNN model to classify normal and abnormal cells with nuclear features. They optimized Deep Pap for comparison. In their work, the weights of the pre-trained model were used to activate the initial weights of the Backbone network. They achieved 91.7% accuracy per image in Mask R-CNN and 87.7% accuracy in the success kernel in another method they used. Song et al. [11] proposed a frame and deformation model based on deep learning technique to correctly classify cervical cells from overlapping clusters. Nithin et al. [12] also proposed a rationale through simulation that an automated system based on the spectrum obtained from a photonic crystal-based biosensor is possible for the detection of cervical cancer. Ghoneim et al. [13] proposed a CNN-ELM-based system to classify cervical cancer cells. In this system, CNN is used to extract deep learned features and then an extreme learning machine (ELM) based classifier input images are classified [14].

2. Material and Method

2.1. The deep learning method used in the study

In the study, automatic classification of 3 different images, koilocytotic, metaplastic and parabasal, taken from the deep learning-based Sipakmed dataset, was performed. VGG16, Inception V3, DenseNet, Xception and InceptionResNetV2 pre-trained networks were used to classify these images based on deep learning.

2.2 Transfer Learning

Transfer learning is a machine learning method in which a machine learning model is trained on a problem and then reused as a starting point for another model [15]. As an example, the purpose of using a model trained with ImageNet dataset with 1000 classes in this study since these networks are pre-trained and learned feature extractions such as edge subtraction in an image, they can perform such operations in a shorter time and the learning speed can increase. There is generally a transfer learning approach in human life. In other words, human beings consciously or unconsciously find a solution to a different event by making use of their past experiences [16]. A lot of data is needed for deep learning models to have high learning performance. Due to the learning transfer structure, this requirement is eliminated and it increases the performance of the model by shortening the learning period. Figure 1 shows the basic working principle of the learning transfer approach. In this study, it is planned to use the learning transfer structure.

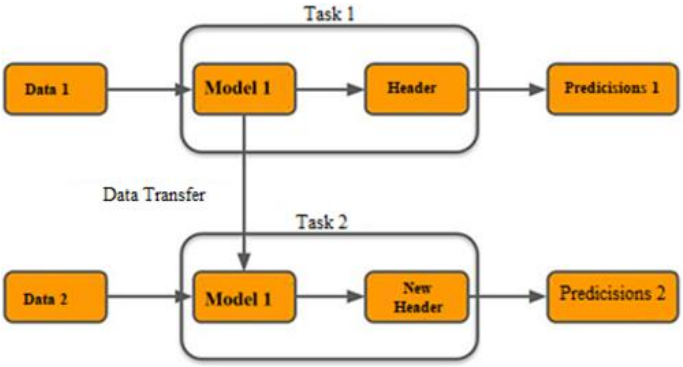

Figure 1. The basic working principle of the transfer learning approach.

2.2.1. VGG16

The VGG16 model is a mesh model developed by the Visual Geometry Group to achieve better results in the ILSVRC-2014 competition [17]. It was proposed by K. Simonyan and A. Zisserman of Oxford University in the article "Very Deep Convolutional Networks for Large-Scale Image Recognition" [18]. Shape. In the VGG16 network architecture presented in Figure 2, there are 13 convolution layers and 5 pooling layers, with a total of 18 layers [17].

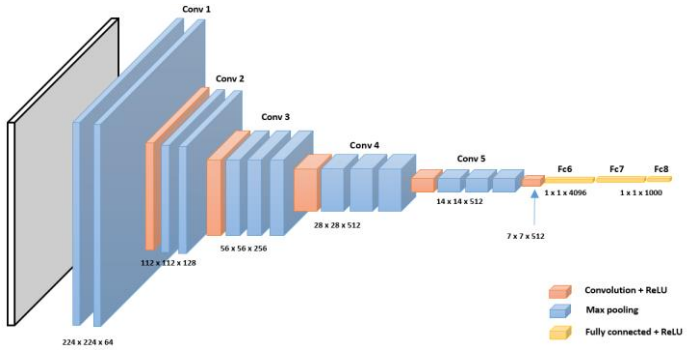

Figure 2. VGG16 Network Structure [4].

2.2.2. Inception V3

Inception V3 is a module featured in the article “Rethinking the Inception Architecture for Computer Vision” [19]. The feature that distinguishes it from Inception V2 is not only the convolution layers, but also the addition of batch-normalized (batch-normalized) and fully connected (FC) layers as auxiliary classifiers. When Inception V2 is arranged this way, it is called Inception V3.

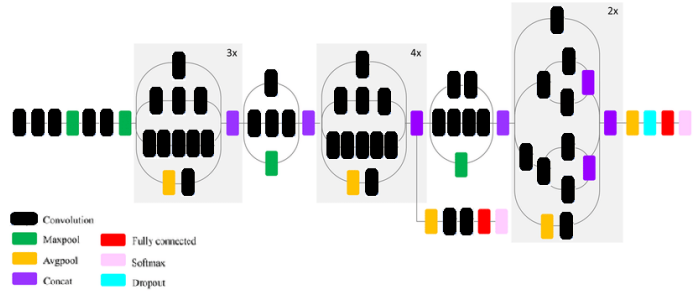

Figure 3. Inception V3 Network Structure [20].

2.2.3. DenseNet

DenseNet consists of 3 basic building blocks, transition layers that support scalability, input and output layers, and dense blocks, which are the most basic components of the algorithm [21]. Simply the DenseNet Architecture aims to solve the problem (object recognition) by heavily interconnecting all layers [22].

Figure 4. DenseNet Network Structure [23].

2.2.4. Xception

The Xception network is basically an evolving network by adding on top of the InceptionV3 network [24]. A normal network creates operations by moving a filter over multidimensional matrices such as width, height and depth in the convolutional section. In this section, the Xception network offers 2 different approaches in addition to the developments in InceptionV3. These are depthwise convolution and pointwise convolution. In the intelligent depth convolution section, it reaches the result by processing only one channel, not every channel. For example, in an image with RGB values, it uses 1 channel, not 3 channels. Since this will cause loss of many features and very unsuccessful results, the classical convolution process is applied as 1x1xChannel Number on the image obtained by processing on 1 channel in smart point convolution and the result is obtained [25].

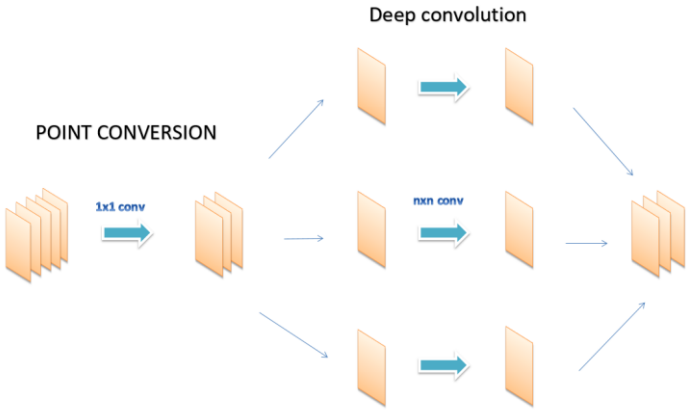

Figure 5. Xception Network Structure [24].

2.2.5. InceptionResNetV2

InceptionResNetV2 is an inception hybrid model with significantly improved recognition performance and increased processing load. InceptionResNetV2 produces the optimum (optimal) result for going both deep and wide [26].

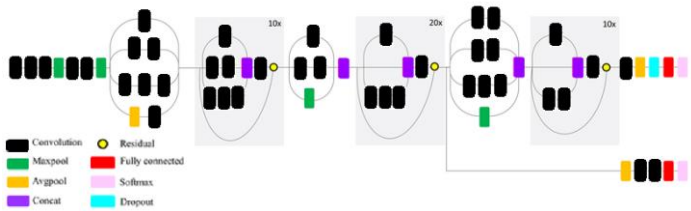

Figure 6. InceptionResNetV2 Network Structure [20].

2.3. Designed GUI

One of the most important differences in this study is that an Graphical User Interface (GUI) has been designed for those who will use Artificial Intelligence algorithms, who have knowledge of this field and who do not have coding knowledge. In the

designed GUI, preprocessing, training and testing processes can be performed.

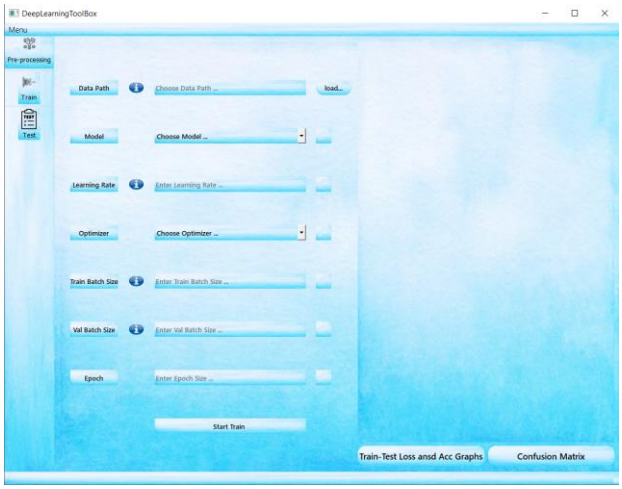

Figure 7. Training Session Image in Application.

On the training screen shown in Figure 7, the user is expected to enter the parameters before performing the training and must determine which pre-trained network to use. Training outputs will be displayed on the blank screen on the right. The user can also see the graphical outputs of the training and the confusion matrix on this screen.

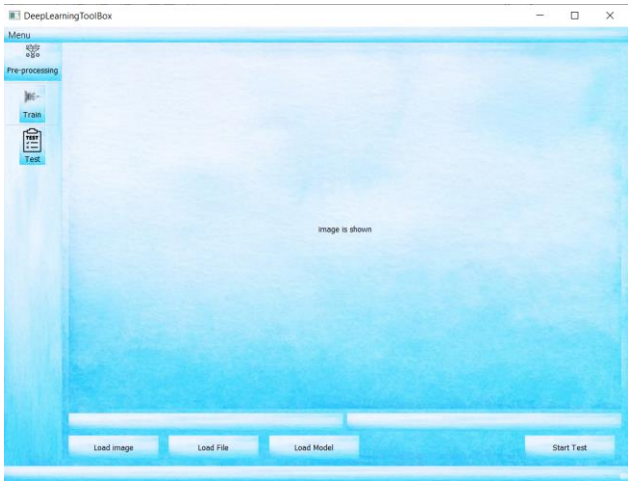

Figure 8. Test Session Image in Application

On the test screen shown in Figure 8, the user uploads the pre-trained model he wants to test to the GUI. In order to test the loaded model in the GUI, it is necessary to upload a picture or a file containing images. After the file is loaded, it can start the test process and see the result on the GUI.

3. Data set used in the paper

Data size is a big factor in deep learning models. The more data, the better the model performs. Within the scope of the study, the SIPAKMED [27] data set was used. In this study, 800 images of koilocytotic cells, 800 images of metaplastic cells and 800 images of parabasal cells were used. Examples of these images are shown in figure 9.

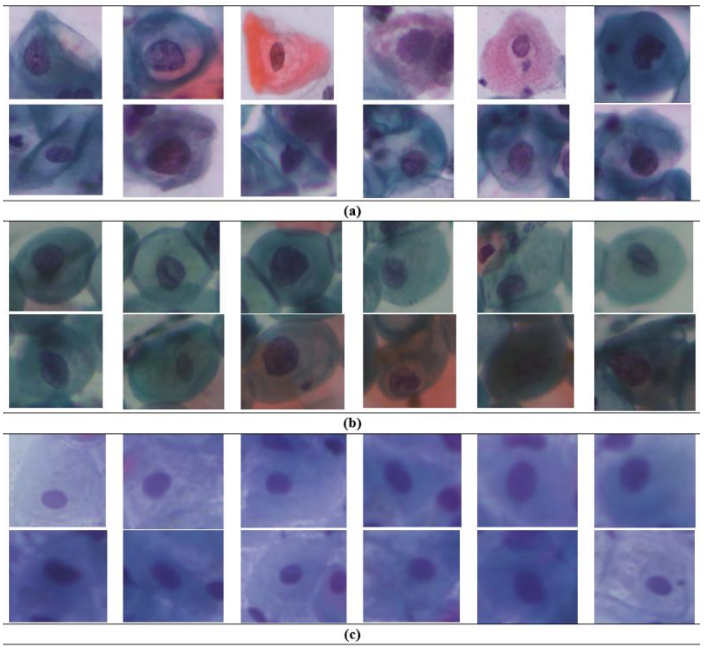

Figure 9. Examples of image classes. (a) Koilocytotic, (b) Metaplastic, (c) Parabasal [27].

4. Experimental study and results

In this study, five different pre-trained networks, namely VGG16, InceptionV3, DenseNet, Xception and InceptionResNetV2, were used and the performances obtained as a result of the experimental studies were compared with each other. The results show that the DenseNet network is more successful in the detection and classification of cancerous and non-cancerous cervical cells.

The training of the models proposed in the study was carried out on a computer with the hardware features shown in Table 1.

Table 1. Hardware specifications of the computer used in the paper.

Unit	Specifications
Memory (RAM)	8 GB
Processor	Intel Core i5 10400F 2.90GHz LGA1200 12MB Cache
Processor Core	12
Graphics Card	NVIDIA GeForce RTX 2080 Ti/PCIe/SSE2
Grap. Card Memory	11 GB GDDR6

Koilocytotic, metaplastic and parabasal images with a resolution of 224x224 shown in Table 2 obtained from the SIPAKMED dataset were used in the study.

Table 2. The number of data ready for training.

Class	Image Number
Koilocytotic	800
Metaplastic	800
Parabasal	800

These images used were divided into training, validation and testing at the rates shown in Table 3. Experimental studies were

carried out using Python programming language and Keras library.

Table 3. Distribution Rates of Data to be Trained

Data	Classification Number of Images (%)
Training	1683 (%70)
Test	482 (%20)
Validation	240 (%10)

As evaluation criteria, confusion matrix, recall, precision and f-1 score were used. The confusion matrix is used to evaluate the performance of a classification model after comparing it with the predictions of a classification model on a set of test data where the true values are known. A confusion matrix example for classification of 1000-element test data consisting of 526 "yes" and 474 "no" values is shown in Table 4.

Table 4. A Confusion matrix example

	Prediction: Yes	Prediction: No
Actual Value: ***Yes***	TP = 452	FN = 22
Actual Value: ***No***	FP = 35	TN = 491

TP (True Positive): It is the case where the estimated value is 1 as well as the actual value.

TN (True Negative): These are the cases where the predicted value is 0 as the actual value is 0.

FP (False Positive): In cases where the actual value is 0 but the predicted value is 1.

FN (False Negative): In cases where the actual value is 1 but the predicted value is 0.

Accuracy: A measure of how often the classifier guesses correctly, in general. Equation 1 shows how accuracy is calculated.

$$Total = TP + TN + FP + FN$$
$$Accuracy = \frac{TP+TN}{Total} \quad (1)$$

Sensitivity, is known as hit rate and is expected to be high. It is a measure of how much TP or TN the classifier has correctly estimated. Equation 2 shows how the sensitivity is calculated.

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

Precision, is a measure of how accurately or incorrectly predicted from all classes. Like sensitivity, sensitivity is expected to be high. Equation 3 shows how precision is calculated.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

f-1 score is a measure of how well the classifier is performing. It is the harmonic mean of sensitivity and sensitivity. Equation 4 shows how the f-1 score is calculated.

$$F1 = 2\,x\,\frac{Precision\ x\ Sensitivity}{Precision+Sensitivity} \quad (4)$$

All networks used in the study were trained for 30 epochs. "Nadam" is used as the optimization function. Training and validation performances and training and validation losses are shown in Figure 10.

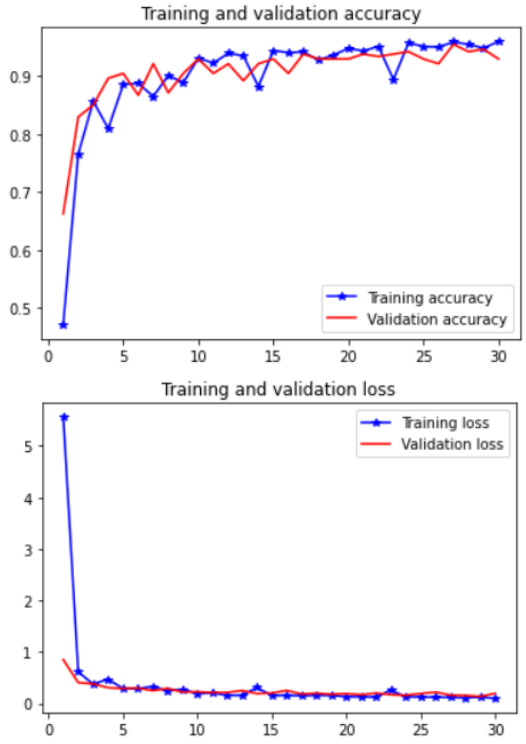

Figure 10. DenseNet training and loss charts.

The precision, recall and F1-score performance results determined in the study presented in Table 5 are shown. According to these results, koilocytotic cells; **Precision** scores are seen as VGG16 and InceptionV3 with the highest. **The Recall** score is seen as DenseNet and Inception ResNet V2. **F1-score** is seen to be the highest in VGG16 network. Metaplastic cells; DenseNet is seen as having the highest **Precision** and **F1-score** scores. **Recall** score is seen as InceptionV3. Parabasal cells; The network with the highest **Precision**, **F1-score and Recall** score is seen as DenseNet.

Table 5. Achievement results after training

Model	Image	Metrics		
		Precision	Recall	F1-Score
VGG16	*Koilocytotic*	0.92	0.95	0.93
	Metaplastic	0.93	0.88	0.91
	Parabasal	0.96	0.97	0.97
	Koilocytotic	0.92	0.92	0.92

InceptionV3	*Metaplastic*	0.91	0.89	0.90
	Parabasal	0.96	0.97	0.97
	Koilocytotic	0.87	0.97	0.92
DenseNet	*Metaplastic*	0.97	0.87	0.92
	Parabasal	0.99	0.98	0.99
	Koilocytotic	0.90	0.94	0.92
Xception	*Metaplastic*	0.96	0.86	0.91
	Parabasal	0.92	0.96	0.94
	Koilocytotic	0.88	0.97	0.92
InceptionResNetV2	*Metaplastic*	0.97	0.86	0.91
	Parabasal	0.97	0.98	0.97

The results presented in Table 6 show all the accuracy, validation accuracy and loss results resulting from the training of the pre-trained networks used in the experimental study. The network with the highest classification performance is seen as DenseNet. It is observed that the performances obtained as a result of InceptionResNetV2 and Vgg16 networks are very close to each other.

Table 6. Training results.

Model	Accuracy	Accuracy verification	Loss
VGG16	0.9357	0.9583	0.1522
InceptionV3	0.9274	0.9000	0.2144
DenseNet	**0.9419**	**0.9541**	**0.1512**
Xception	0.9212	0.9416	0.2487
InceptionResNetV2	0.9378	0.9333	0.1858

Figure 11 shows the confusion matrix of the DenseNet model with the highest training result. When this matrix is examined, it is seen that the DenseNet network correctly classified 160 of the koilocytotic cells, misclassified 4 images as metaplastic and 1 image as parabasal. It is seen that Parabasal cells classified 155 correctly and 3 incorrectly as koilocytotic. He misclassifies 139 of the metaplastic cells as correct and 20 as koilocytotic.

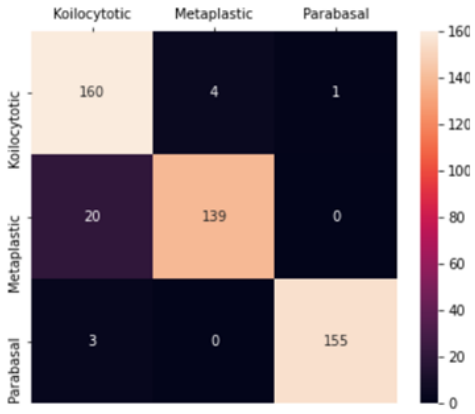

Figure 11. Confusion matrix of DenseNet model with the highest training result.

It has been observed that the DenseNet network best classifies parabasal cells first and then classifies koilocytotic cells. It is observed that the most classification errors are made in metaplastic cells. In order to reduce this error, metaplastic cell images can be increased during the training phase of the networks. Another reason is that metaplastic cells are very similar to both koilocytotic and parabasal cells.

5. Conclusions

In the study, koilocytotic, metaplastic and parabasal images in Sipakmed dataset were classified using VGG16, InceptionV3, DenseNet, Xception and InceptionResNetV2 pre-trained network models to detect cervical cancer. Koilocytotic cells are the most common and are very similar in properties to metaplastic cells. Morphological features of parabasal cells and metaplastic cells are very close to each other. Since it is very important to separate these three data sets from each other, the relevant data sets are emphasized. In addition, an GUI has been developed to provide ease of use to healthcare professionals working in this field. Using this developed GUI VGG16, InceptionV3, DenseNet, Xception and InceptionResNetV2 pre-trained networks, training can be made to classify different datasets or classification processes can be performed using trained models. The highest accuracy rate among the classified models was obtained with the DenseNet model with 94.19%.

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