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Skin Cancer Classification into Three Classes

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Abstract – The incidence of skin cancer is increasing. Early detection of cases of skin cancer is vital for treatment. Recently, computerized methods have been widely used in cancer diagnosis. These methods have important advantages such as no human error, short diagnosis time, and low cost. Melanoma is most dangerous type of skin cancer. Basal cell carcinoma is type with high cancer potential. Properly classified images can help doctors predict the type of skin cancer. This study aims to classify into three classes, including the normal type.

Keywords – Deep learning, skin cancer, image classification, ResNet, LinkNet

I. GİRİŞ

Cancer is one of the most common cause of death worlwide. In 2040, it is estimated that around 16 million people will die of cancer [1]. Skin cancer has different types such as melanoma, suqamous cell carcinona, basal cell carcinona, nevus lesions. Melanoma is most dangerous type. Most of skin cancer deaths are due to melanoma (About 63%). In 2021, there was 115320 new skin cancer cases In the United States. 11540 cases resulted in death [2].

Early detection of skin cancer increases the probability of cure to 95% [3]. There are classic method such ABCD rule, dermocopy to detect skin cancer [5]. These methods are both time consuming and costly. In addition, success in these methods remains between 75-84% [6, 7].

There are many difficulties in the classification of skin cancer, such as color transitions on the lesion, glare, and the shape of the lesion. In the study presented by Kaur, Gholamhosseini, Sinha, and Lindén (2022), a 90.4% educational success value was obtained with the DCNN model on the ISIC2020 dataset. No noise cleaning or segmentation was performed on the lesions. Two classes, melanoma and normal, were used for lesion classification [36]. In one study, it was emphasized that training with segmented images was more successful. The reason for the lower success in the classification made with the unsegmented image; reduction of the area of the lesion in the image and noises that could not be cleared (brightness, hair noise, etc.). A dice accuracy of 85.19% was obtained in the classification with SVM [37].

Indraswari, Rokhana and Herulambang (2022) used the MobileNetV2 model to classify skin cancer lesions. Noise cleaning and lesion segmentation were not included in the study. They achieved a training success of 85% in the ISIC-archive dataset and 83% in the ISBI2016 dataset. Two classes of lesions, malignant and benign, were also used in this study [38]. In the DCNN-based deep learning model presented by Ali, Haque, Miah, and Rahman (2021), 92.69% educational success was achieved. Lesions are classified as benign and malignant. In the study, noise cleaning was performed with image processing algorithms [39].

In the literature, skin cancer images are generally divided into two as benign and malignant. There are also examples where it is divided into more classes. In the study of Kausar et al. (2021), skin cancer was divided into eight classes by deep learning. ResNet, DenseNet, VGG16 and Inception V3 models were used in the study. Among these, the highest success rate was obtained with ResNet (92% educational success).

Looking at the literature, it is seen that skin cancer is generally divided into benign and malignant. In this study, lesions were divided into eight classes available in the literature. These; Basal cell carcinoma, benign, malignant, dermatofibroma, actinic keratosis (AK), melanocytic nevi (MN), squamous cell carcinoma (SHC), vascular lesions (VL) [40].

Kahn, Akram, Sharif, Kadry, and Nam (2021) developed a DDS for classification of skin cancer. In the study, in which the lesions were divided into eight classes, the ISBI2019 dataset achieved 85.3% educational success. 70% of the dataset is reserved for training and testing. Noise cleaning and interface were not mentioned in the study [50].

Kahia, Echtioui, Kallel and Hamida (2022) used different deep learning models in classification skin cancer. In this study, they used two classes, benign and malign. 73.33% accuracy was obtained [9].

Kartal and Polat (2022) classified the lesions as benign and malignant with a modified ResNet101 model. In the study using ISIC2017 dataset, 91% F1-score, 91% sensitivity, 91% precision and 91.36% training success were achieved [X].

II. Materials and Method

A. Datasets

ISIC2018 HAM10000 dataset with 7 different class labels was used for lesion classification. In this data set, there are a total of 10015 labeled colored images. This dataset was named the lesion classification dataset.

There are different numbers of data labeled melanoma (MEL), BCC, normal (remaining types) used in the classification phase in the data set. The numbers were balanced with data augmentation (DA) methods to normalize the data distribution. The dataset is divided into 70% training, 20% validation, and 10% testing.

Table 1. Distribution of dataset

Type	**MEL**	**BCC**	**Normal**
Count	1113	514	8388
DA	4452	2056	8388
Training (%70)	3116	1439	5871
Valiation (%20)	891	561	1679
Test Dataset (%10)	445	51	838

Images have 256x256x3 size as input. Algorithm was run 500 epoch. Binary cross entropy as output function adn adam as optimizer were used in training stage.

B. Proposed Model

ResNet50 with imagenet was used as classification model [Y]. Proposed model can be seen in figure 1.

```
from keras.callbacks import CSVLogger, ModelCheckpoint
csv_logger = CSVLogger('log.csv', append=True, separator=';')


filepath = "best_model.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_acc', verbose=1, save_best_only=True, mode='max')
callback_list = [csv_logger, checkpoint]

def cihan():



    training_shape = (256,256,3)
    base_model = ResNet50(include_top=False,weights='imagenet',input_shape = training_shape)
    for layer in base_model.layers:
        layer.trainable = True

   n_classes = 2



    model = Flatten()(model)
    model = Dense(128)(model)
    model = Dropout(0.5)(model)
    model = BatchNormalization()(model)
    model = Activation('relu')(model)
    output = Dense(n_classes, activation='softmax')(model)
    model = Model(inputs=base_model.input, outputs=output)



    skip=d4
    x = Conv2D(64, 3, padding="same")(d4)
    x = BatchNormalization()(x)
    x = Activation("relu")(x)
    x = Conv2D(64, 3, padding="same")(inputs)
    x = BatchNormalization()(x)
    x = Activation("relu")(x)
    x = Concatenate()([x, skip])
    outputs = Conv2D(1, 1, padding="same", activation="sigmoid")(x)


    return model
```

Figure 1. Proposed Model Python Codes

Classification has following steps.

Step 1: The classification dataset is divided into training: 7151 and validation: 2041, testing: 1020.

Step 2: The Model 250 epoch was run.

Step 3: Estimations were made on the test data with the trained models.

3. RESULTS

The training results obtained using different models are shown in Table 3.

Parameter	UNet	MobileNetV2	**Proposed Model**
Accuracy (%)	95,73	97,13	**97,95**
Validation Accuracy (%)	92,85	94,41	**95,39**
Dice coefficient (%)	93,24	93,28	**96,12**

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