Article Title

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Abstract

People still are suffering from pain due to this frequent misidentification of diseases related to skin. For the advanced deep learning methodology of classification of skin diseases, this study uses the convolutional neural networks (CNNs). This has been done by applying the pre-trained DenseNet201 and VGG16 and Resnet152v2 models on the images of skins. Data augmentation was performed to reduce overfitting of the model and enhance the robustness of the same. Using criteria including accuracy, precision, recall, F1 score, the models' performance was evaluated; all showed promising results for clinical use. Moreover, the study delves into model interpretability, where it is discussed how well the models can predict new, unexplored cases. This would help in the proper diagnosis, and thus the correct distinction between skin disorders, thus reducing the number of false diagnoses and enhancing patients' long-term comfort.

Keywords: Skin disorders, deep learning, convolutional neural networks, ResNet152V2, DenseNet201, VGG16, data augmentation, model evaluation

1 Introduction

Skin diseases affect millions globally and pose challenges for timely and accurate diagnosis. Traditional methods, reliant on visual examination by dermatologists, can lead to delays and disagreements. However, advancements in deep learning, a branch of artificial intelligence, have transformed medical image analysis in dermatology.

Deep learning automatically learns complex patterns in data. Therefore, the technique has been found highly effective for analyzing dermatological images. Convolutional Neural Networks are known for being a success in image recognition; these networks identify various skin conditions such as acne, melanoma, eczema, and psoriasis very well. Techniques such as transfer learning utilize pre-trained models on large datasets, hence improving the performance of models, especially when there is limited availability of labeled medical data.

Deep learning improves the diagnostic accuracy and workflow efficiency and helps healthcare professionals make better decisions and achieve better outcomes for patients. Real-time applications, available through online and mobile apps, also allow remote diagnostics, thereby bridging the gaps in access and geography.

However, there are ethical concerns in relation to patient privacy, security of data, and the collaboration between technology and health professionals. This paper explores how deep learning can improve the classification of skin conditions and assist practitioners in delivering accurate diagnoses and better patient care.

2 Literature Survey

The paper highlights the advancements that deep learning and image processing have provided in the identification of skin diseases, but CNN-based techniques are particularly significant. Notable advances include wavelet transformations, metaheuristic-based feature selection, HOG for feature extraction, and IoT integration. With remarkable accuracy rates of up to 99.33%, CNN designs like ResNet50 and Inception v3 are capable of accurately diagnosing illnesses including benign keratosis, melanoma, and dermatitis. These results are further enhanced through transfer learning and fine-tuning. The present systems offer scalable, accurate, and cost-effective dermatological diagnosis solutions that combine AI, IoT, and complex algorithms.

3 Approach

This section outlines the steps used to prepare the data, set up the model, compile the results, and train the skin disease prediction model.

Table 1: Summary of Algorithms, Techniques, and Accuracy of Different Research

Paper	Model/Technique	Accuracy (%)
Our Paper	DenseNet201, ResNet152V2, VGG16 (Ensemble)	86% (Fusion), 75 (VGG16), 82 (ResNet152V2), 78 (DenseNet201)
[1]	CNN-SVM-MAA	Not Mentioned
[2]	CNN for BK, AC, DF	72 (BK), 77 (AC), 69 (DF)
[3]	Frequency Impedance Analysis	75
[4]	CNN + IoT	Not Mentioned
[5]	CNN + Augmentation	Not Mentioned
[6]	Proposed Model, VGG16, ResNet50	91.07 (Proposed), 87.64 (VGG16), 73.56 (ResNet50)
[7]	Decision Tree + Texture Features	Not Mentioned
[8]	ResNet50, Inception V3, VGG19, AlexNet	90.2 (ResNet50), 72.1 (Inception V3), 50.27 (VGG19)
[9]	Xception, CNN, VGG16, Inception V3	99.33 (Xception), 97.78 (VGG16), 98.97 (Inception V3)
[10]	CNN + SVM	Not Mentioned
[11]	EfficientNet	97.2 (ISIC 2019), 97.1 (Dermnet)
[12]	SVM, KNN, RF, NB	97.33
[13]	Inception V3	84 (Validation), 80 (Test)
[14]	MobileNet + Transfer Learning	95
[15]	ResNet50	91.71

3.1 Dataset Description

The dataset used in this study consists of 10,000 samples, categorized into 6 main classes:

- **Enfeksiyonel:** 1,000 samples
- **Ekzama:** 1,000 samples
- **Akne:** 1,000 samples
- **Pigment:** 1,000 samples
- **Benign:** 1,500 samples
- **Malign:** 1,000 samples

3.2 Preparing Data

To enhance variety and generalization, the dataset—which is separated into six groups (Enfeksiyonel, Ekzama, Akne, Pigment, Benign, and Malign)—goes through preprocessing:

- Image Rescaling: Pixel values in the image are resized to fall between [0, 1].
- Data Augmentation: To reduce overfitting and improve model resilience, techniques including rotation, zooming, and horizontal flipping are applied. Data Splitting: To evaluate performance, the dataset is divided into training, validation, and testing sections.

3.3 Model Configuration

The model uses pre-trained weights and extra layers for fine-tuning to merge DenseNet201, ResNet152V2, and VGG16:

- Dense Layers: Extra layers transform features into classifications of skin diseases.
- Feature Fusion: The outputs of the three CNNs are combined to provide a comprehensive feature representation. Dropout Regularization: During the training phase, dropout layers assist avoid overfitting.

3.4 Model Compilation

These parameters are used to construct the model:
- Optimizer: An initial learning rate of 0.001 is used when using the Adam optimizer.
- Loss Function: For multi-class classification, categorical cross-entropy is used. Metrics Accuracy is a metric used to evaluate the proportion of properly categorized photos.

3.5 Model Training

The prepared dataset is used to train the model, and parameters are repeatedly optimized through validation:

- Batch Processing To maximize resource use, the training is carried out in batches.
- Learning Rate Reduction: To guarantee steady training, the learning rate is dynamically adjusted.
- Early Stopping: After a predetermined number of epochs, training is stopped if validation loss does not improve.

The test set is used to evaluate the model's accuracy and generalization after training.

4 Proposed Methodology

The suggested system combines data preprocessing, model training, and a web-based user interface to enable precise classification of skin diseases.

4.1 Data Preprocessing and Augmentation

The Skindisease 2022 dataset is processed to standardize pixel values (rescaled by 1/255) and augmented (zoomed by 0. 2 and flipped horizontally) to enhance model generalization.

4.2 Fusion Model Development

At the heart of the system is a fusion model that merges DenseNet201, ResNet152V2, and VGG16. Each pre-trained CNN model is responsible for extracting features, which are subsequently combined for a unified representation.DenseNet201 and VGG16 utilize ImageNet pre-trained weights with additional global average pooling and dense layers (with 512 neurons, using ReLU).ResNet152V2 trains its layers starting from the 140th layer, maintaining comparable pooling and dense setups.Fusion Layers: The concatenated outputs are processed through dense layers (with 128 and 32 neurons utilizing ReLU), dropout layers (with a rate of 0. 2), and an output layer (with 6 neurons using softmax activation).

5 Mathematical Modeling

The skin disease prediction problem is modeled as a multi-class classification task using deep learning techniques. The mathematical operations for key components are outlined below.

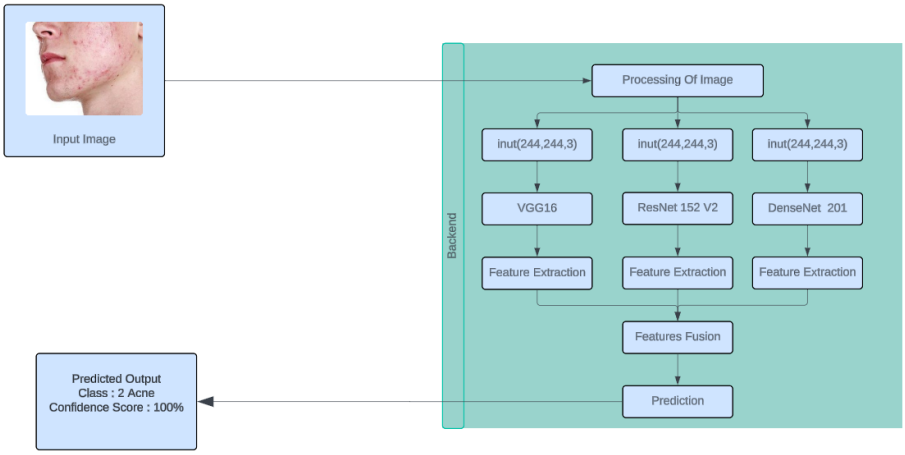


Fig. 1: Technologies Used

5.1 Convolutional Neural Networks (CNNs)

CNNs extract features using convolution, pooling, activation, and normalization operations:
ReLU Activation:

$$f(x) = \max(0, x)$$

Pooling (Max Pooling):

$$P_{max}(x, y) = \max_{i,j}\{I(x + i, y + j)\}$$

Batch Normalization:

$$\hat{x} = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}}, \quad y = \gamma\hat{x} + \beta$$

where μ is the mean, σ^2 the variance, and γ, β are learnable parameters.

5.2 Fusion Model Architecture

As mentioned earlier, three pre-trained CNNs, DenseNet201, ResNet152V2, and VGG16, are fused in the proposed model. Each of the pre-trained models takes the input image $X \in \mathbb{R}^{256\times256\times3}$ for feature maps extraction.

- **DenseNet201**:

$$F_{dense} = \text{DenseNet201}(X)$$
$$G_{dense} = \text{GlobalAveragePooling2D}(F_{dense})$$
$$D_{dense} = \text{Dense}(512, \text{activation='relu'})(G_{dense})$$

- **ResNet152V2**:

$$F_{resnet} = \text{ResNet152V2}(X)$$
$$G_{resnet} = \text{GlobalAveragePooling2D}(F_{resnet})$$
$$D_{resnet} = \text{Dense}(512, \text{activation='relu'})(G_{resnet})$$

- **VGG16**:

$$F_{vgg} = \text{VGG16}(X)$$
$$G_{vgg} = \text{GlobalAveragePooling2D}(F_{vgg})$$
$$D_{vgg} = \text{Dense}(512, \text{activation='relu'})(G_{vgg})$$

5.3 Fusion of Features

The outputs of the three models are concatenated to form a comprehensive feature vector:

$$F_{fusion} = \text{Concatenate}([D_{dense}, D_{resnet}, D_{vgg}])$$

This vector is then passed through additional dense layers and dropout layers to enhance the model's learning capacity and prevent overfitting:

$$H_1 = \text{Dense}(128, \text{activation='relu'})(F_{fusion})$$

$$H_1 = \text{Dropout}(0.2)(H_1)$$
$$H_2 = \text{Dense}(32, \text{activation='relu'})(H_1)$$
$$H_2 = \text{Dropout}(0.2)(H_2)$$

5.4 Output Layer

The final dense layer maps the processed features to the six skin disease classes using the softmax activation function:

$$Y = \text{Dense}(6, \text{activation='softmax'})(H_2)$$

The softmax function converts the output logits into probabilities:

$$P(y_i) = \frac{e^{y_i}}{\sum_{j=1}^{6} e^{y_j}}$$

where y_i is the logit for class i, and $P(y_i)$ is the predicted probability for class i.

5.5 Loss Function and Optimization

The model is trained using the categorical cross-entropy loss function:

$$L = -\sum_{i=1}^{N}\sum_{j=1}^{6} y_{ij} \log \hat{y}_{ij}$$

where N is the number of samples, y_{ij} is the binary indicator (0 or 1) if class label j is the correct classification for sample i, and $\hat{y}_{ij}$ is the predicted probability of sample i being in class j.

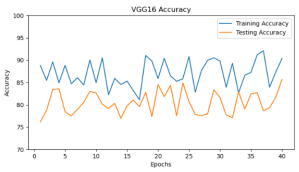
The Adam optimizer is used to minimize the loss function, updating the model weights iteratively based on the gradients computed during backpropagation.

6 Output Images

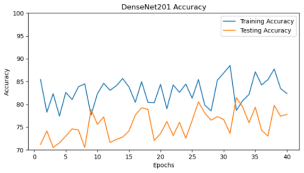
(a) Web Application

(b) Another View of Web Application

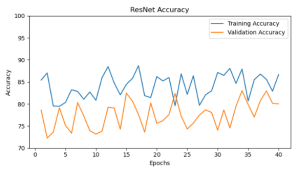
(c) web application



(d) VGG16 Accuracy&loss



(e) Densnet201



(f) Resnet

Fig. 2: Output images showcasing the web application, flow charts, and system architecture.

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8 Conclusion

It has presented a skin disease prediction system that has used an ensemble of DenseNet201, ResNet152V2, and VGG16 models, which obtained an accuracy of 86% on the validation dataset. It outperforms the single models comprising VGG16 with 75%, ResNet152V2 with 82%, and DenseNet201 with 78%. The fused model improves the extraction and classification performance, thus showing that multiple architecture combinations work well.Using the embedding model in a web application using Flask increases accessibility by allowing the user to upload a skin stroke image and receive a prediction- location. This practical implementation demonstrates the potential of this model to revolutionize dermatological diagnosis and opens up opportunities for the future field to increase model robustness, data augmentation and validation.

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