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ScabAI: A Deep Learning-Based Mobile Application for Scabies Detection from Skin Images

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Anahtar Kelimeler

Uyuz
Derin Öğrenme
CNN
Mobil Arayüz
Erken Tanı

Graphical/Tabular Abstract (Grafik Özet)

ScabAI is a CNN-based mobile application that classifies scabies and non-scabies skin lesions with high accuracy. It enables users to upload or capture images and receive rapid diagnostic predictions. / ScabAI, uyuz ve uyuz olmayan cilt lezyonlarını yüksek doğrulukla sınıflandıran CNN tabanlı bir mobil uygulamadır. Kullanıcıların görsel yüklemesini veya çekmesini sağlayarak hızlı tanı sunar.

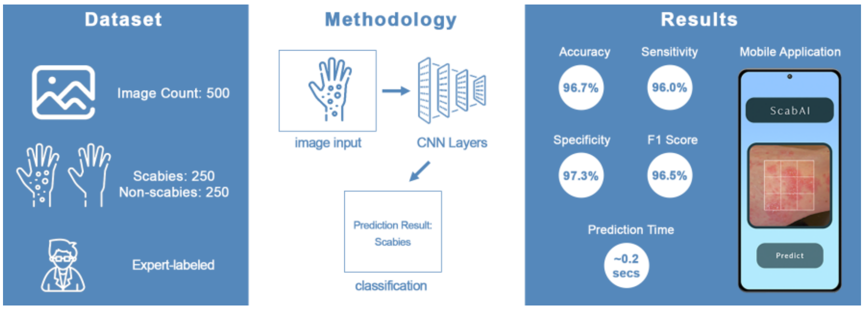

***Figure A**: Graphical abtract / **Şekil A:**.Grafik özet*

Highlights (Önemli noktalar)

- *The model achieved 96.7% accuracy in scabies detection. / Model, uyuz tespitinde %96,7 doğruluk elde etmiştir.*
- *A user-friendly mobile interface was developed using React Native. / React Native ile kullanıcı dostu bir mobil arayüz geliştirilmiştir.*
- *The application supports early diagnosis through image-based prediction. / Uygulama, görüntü tabanlı tahminle erken tanıyı desteklemektedir.*

***Aim (Amaç):** This study aims to develop a deep learning-based mobile application to detect scabies from skin images. / Bu çalışma, cilt görüntülerinden uyuz tespitine yönelik derin öğrenme tabanlı bir mobil uygulama geliştirmeyi amaçlamaktadır.*

***Originality (Özgünlük):** Unlike previous studies, a fully functional mobile interface is integrated with the trained CNN model. / Önceki çalışmalardan farklı olarak, eğitilmiş CNN modeli ile entegre edilmiş işlevsel bir mobil arayüz geliştirilmiştir.*

***Results (Bulgular):** The proposed model achieved 96.7% accuracy, 96% sensitivity, 97.3% specificity, and 96.5% F1 score.. / Önerilen model %96,7 doğruluk, %96 duyarlılık, %97,3 özgüllük ve %96,5 F1 skoru elde etmiştir.*

***Conclusion (Sonuç):** The mobile application ScabAI provides accurate preliminary diagnoses, supporting early treatment. / ScabAI mobil uygulaması, doğru ön tanı sağlayarak erken tedaviyi desteklemektedir.*

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Abstract

Scabies, a contagious skin disease caused by the Sarcoptes scabiei mite, remains a significant public health concern globally. This study aims to develop a mobile application, ScabAI, which uses a deep learning model based on Convolutional Neural Networks (CNNs) to detect scabies from skin images. The model was trained using a dataset of 500 images, divided equally between scabies and non-scabies cases, and achieved high performance metrics, including 96.7% accuracy, 96% sensitivity, 97.3% specificity, and a 96.5% F1 score. These results demonstrate the model's reliability and effectiveness in detecting scabies, outperforming many existing models. The mobile application allows users to capture or upload images of suspected scabies lesions, providing rapid and accurate preliminary diagnoses. ScabAI offers a practical, user-friendly tool that can be beneficial for both healthcare providers and individuals, supporting early detection, timely treatment, and reducing the risk of disease transmission. This study underscores the potential of integrating artificial intelligence with mobile platforms for improved dermatological care, particularly in resource-limited settings. Future research should focus on expanding the dataset to enhance generalization and exploring additional AI techniques to refine detection accuracy. ScabAI not only contributes to AI-assisted dermatology but also serves as a scalable model for developing similar tools targeting other skin conditions. This innovative approach addresses both clinical needs and user accessibility, advancing healthcare outcomes and public health initiatives.

ScabAI: Cilt Görüntülerinden Uyuz Tespiti için Derin Öğrenme Tabanlı Mobil Uygulama

Makale Bilgisi

Araştırma makalesi
Başvuru: 16/12/2024
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Anahtar Kelimeler

Uyuz
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Erken Tanı

Öz

Uyuz hastalığı, Sarcoptes scabiei akarının neden olduğu bulaşıcı bir cilt hastalığı olup, dünya genelinde önemli bir halk sağlığı sorunu olmaya devam etmektedir. Bu çalışma, cilt görüntülerinden uyuz hastalığını tespit etmek amacıyla Derin Öğrenme tabanlı bir mobil uygulama olan ScabAI'yi geliştirmeyi amaçlamaktadır. Uygulamanın temelinde, Konvolüsyonel Sinir Ağları (CNNs) tabanlı bir derin öğrenme modeli bulunmaktadır. Model, 500 görüntüden oluşan bir veri seti üzerinde eğitilmiş; bu veri seti uyuz ve uyuz olmayan vakalar arasında eşit şekilde dağıtılmıştır. Model, %96,7 doğruluk, %96 duyarlılık, %97,3 özgüllük ve %96,5 F1 skoru gibi yüksek performans metrikleri elde etmiştir. Bu sonuçlar, modelin uyuz tespitindeki güvenilirliğini ve etkinliğini ortaya koymakta ve mevcut birçok modelin performansını aşmaktadır. Mobil uygulama, kullanıcıların şüpheli uyuz lezyonlarının görüntülerini çekmesine veya yüklemesine olanak tanıyarak hızlı ve doğru bir ön tanı sağlamaktadır. ScabAI, erken teşhisi destekleyerek, zamanında tedaviye olanak tanıyan ve hastalık bulaşma riskini azaltan pratik ve kullanıcı dostu bir araç sunmaktadır. Bu çalışma, yapay zekanın mobil platformlarla entegre edilerek dermatolojik bakımda iyileştirmeler sağlama potansiyelini vurgulamaktadır; özellikle kaynakların sınırlı olduğu bölgelerde önemli bir çözüm sunmaktadır. Gelecekteki araştırmalar, genelleştirmeyi iyileştirmek için veri setinin genişletilmesine ve tespit doğruluğunu artırmak amacıyla ek yapay zeka tekniklerinin keşfine odaklanmalıdır. ScabAI, yalnızca yapay zeka destekli dermatolojiye katkı sağlamakla kalmayıp, diğer cilt hastalıklarını hedefleyen benzer araçların geliştirilmesi için ölçeklenebilir bir model işlevi görmektedir. Bu yenilikçi yaklaşım, hem klinik ihtiyaçları hem de kullanıcı erişilebilirliğini karşılayarak sağlık hizmetleri sonuçlarını ve halk sağlığı girişimlerini ileriye taşımaktadır.

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1. INTRODUCTION (GİRİŞ)

Scabies is a contagious skin infection caused by the mite Sarcoptes scabiei. The mite is nearly invisible to the naked eye, burrowing into the epidermis where it lays eggs, triggering an intense immune response from the host that leads to severe itching, even with just a few mites present [1]. Scabies is a globally prevalent condition affecting individuals of all ages and genders, significantly diminishing quality of life. It is estimated that approximately 130 million people worldwide are affected by scabies. In 2009, the World Health Organization (WHO) designated scabies as a neglected skin disease, and it remains a major public health issue in many developing countries [2]. Recent reports indicate an increase in the number of scabies cases in Turkey. The country's overall case growth rate was 81% in 2018 and 138% in 2019. In a single-center study conducted in Turkey, a nearly sevenfold increase in cases was observed in 2018 compared to 2017, with a 30-fold increase reported in 2019 [3], [4].

Scabies is highly contagious and can easily spread to others through direct contact or by sharing personal items. The affected areas often present as red rashes, which are recognized as scabies bites. Symptoms may take more than six weeks to appear, and the most common areas of infestation include spaces between the fingers, elbows, nipples, and wrists. Scabies can also manifest on the head, face, neck, and other parts of the body. The mite is so small that it can live on the skin for months, laying eggs during this time. Though typically invisible to the naked eye, it induces itching, and because of its high contagiousness, early detection and appropriate treatment are essential to control its spread and mitigate the condition.

Scabies is frequently misdiagnosed as other pruritic skin conditions such as eczema, impetigo, tinea corporis (ringworm), and psoriasis [5]. For example, a study conducted in Brazil revealed that 18% to 43% of children diagnosed with eczema were actually suffering from scabies [6].

Skin diseases are very common today; some are simple and easy to treat, while others can be highly harmful and potentially incurable. Therefore, comprehensive care for this vital organ, the skin, is essential. Diagnosing skin diseases can be complex, particularly when two or more conditions exhibit the same or similar symptoms. As a result, diagnosing skin diseases often requires the expertise of a dermatologist with extensive experience in this field [7]. However, the introduction of artificial intelligence into healthcare has significantly improved the diagnosis of skin diseases, as well as other medical conditions [8].

With the advent of machine learning, diagnosing skin diseases has become easier for many dermatologists. Approaches involving Computer Vision, Machine Learning, and Artificial Intelligence have been introduced to accurately identify diseases based on clinically assessed histopathological characteristics.

Currently, there are five popular areas where machine learning applications are being utilized in dermatology: (1) Precision Medicine, (2) Classifying skin diseases using clinical images, (3) Classifying skin diseases using dermatopathology images, (4) Classifying skin diseases using smartphone applications and monitoring devices, and (5) Facilitating scientific research on widespread epidemic diseases [9], [10].

Machine learning has also become a powerful tool for predicting and assessing scabies. Various studies have demonstrated the effectiveness of machine learning algorithms in this area.

Research developed by Yasir et al. introduce an automated system to detect nine dermatological diseases, including scabies, using image processing techniques and a feed-forward artificial neural network (ANN). Scabies detection was a key focus, with the system achieving an 89% detection rate for this condition. The system analyzed 277 images of scabies patients and successfully classified 246 of them. The process involves pre-processing skin images using eight algorithms to extract significant features such as infected area size, shape, and color. In addition, user inputs like gender, age, and symptoms (e.g., itching) were incorporated into the ANN. Overall, the system showed a detection accuracy of 90%, with scabies ranking among the higher-detection conditions, reflecting the system's reliability in recognizing diseases with specific visual patterns [11].

Parikh et al. explore the diagnosis of common skin diseases such as bacterial infections, fungal infections, eczema, and scabies using soft computing techniques, specifically Artificial Neural Networks (ANN) and Support Vector Machines (SVM). The dataset includes 470 patient cases, with 87 of them being scabies cases. The models were trained using a range of 47 features, including clinical symptoms and environmental factors. ANN achieved a higher accuracy compared to SVM, with an accuracy of 97.17% and an F-score of 0.9419 in the 80-20% training-testing partition. For scabies

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detection specifically, the research emphasizes that the inclusion of clinical symptoms like itching and environmental factors such as humidity improved the model's accuracy [12].

The research by Arifin et al. focuses on developing an automated dermatological disease diagnostic system using color-skin images and machine learning techniques, specifically feed-forward backpropagation artificial neural networks (ANN). The system was tested on 704 images, detecting six different dermatological diseases, including scabies, with a total of 2055 affected regions identified. Scabies detection achieved a high classification accuracy of 98.67%, with 507 images being analyzed for the disease. The system uses color image processing, k-means clustering, and color gradient techniques to identify diseased skin areas and extract key visual and patient history features. Overall, the system exhibited a skin anomaly detection accuracy of 95.99% and a disease classification accuracy of 94.016% [13].

Akyeramfo-Sam et al. present a web-based skin disease detection system, "medilab-plus," using convolutional neural networks (CNN) for diagnosing atopic dermatitis, acne vulgaris, and scabies, prevalent in Ghana. The system was built using the TensorFlow framework and achieved classification accuracies of 88% for atopic dermatitis, 85% for acne vulgaris, and 84.7% for scabies. It demonstrated a prediction time of 0.0001 seconds, allowing a dermatologist to potentially diagnose up to 1,440 patients per day. The system was tested using 254 images collected from four medical centers. The researchers highlighted that the system offers faster and more accurate diagnosis compared to traditional methods, with a focus on enhancing dermatological services in Ghana [14].

Another study by Akmalia et al. integrates Local Binary Pattern (LBP) and Convolutional Neural Network (CNN) to classify skin diseases from digital images, including scabies, dermatitis, abscess, herpes, urticaria, and pyoderma. By analyzing texture, shape, and color features in skin images, the system achieved a high average classification accuracy of 92%. For scabies, the system demonstrated an impressive accuracy of 90%, effectively identifying this disease, which is characterized by symptoms like red spots, itching, and inflamed skin. The integration of LBP for feature extraction and CNN for classification led to better overall performance compared to using CNN alone. The research involved training with 60 images and testing with 12 images, achieving accuracies between 80-100% for different diseases, proving the system's value for early detection and diagnosis of skin diseases [15].

The research by Bajwa et al. explores the use of deep neural networks (DNNs) to create a computer-aided diagnosis (CAD) system for skin diseases, focusing on classifying hundreds of conditions, including scabies. The system was trained on two large datasets—DermNet and the ISIC Archive. On the DermNet dataset, the system achieved 79.94% Top-1 accuracy and 98.07% Area Under the Curve (AUC) for classifying 23 super-classes of diseases, including scabies, which saw an F1 score of 73.91% in one experiment. On the ISIC Archive, the system demonstrated a high 93.06% Top-1 accuracy and 99.23% AUC for classifying seven diseases. The study emphasizes the potential of DNNs to achieve near-human accuracy in detecting a wide range of dermatological conditions [16].

Mohammed & Al-Tuwaijari present a machine learning-based skin disease classification system that relies on various algorithms to enhance diagnostic accuracy. By analyzing both images and tissue features, the system is able to classify skin diseases, including scabies, which is highlighted for its particular impact. The accuracy for classifying scabies and other conditions using image processing methods ranged from 50% to 100%, with tissue analysis methods achieving over 94% accuracy. Scabies, in particular, is emphasized due to its contagious nature and the significance of early diagnosis for effective treatment. The study surveyed several systems and algorithms, concluding that using image processing in conjunction with machine learning can provide reliable diagnostics [17].

Halder et al. focuses on the automated detection of scabies using image processing and Convolutional Neural Networks (CNN). Scabies, a contagious skin disease affecting millions globally, is detected using a dataset of 1,817 images. The methodology includes applying various data augmentation techniques such as cropping, rotation, and brightening to enhance the dataset. Image segmentation is performed using a thresholding technique to isolate the infected areas, followed by feature extraction through CNN. The system outperforms previous methods, achieving 98.97% validation accuracy and 97.25% testing accuracy. This study emphasizes the significance of early scabies detection, particularly given the disease's high prevalence and contagious nature [18].

In conclusion, machine learning algorithms stand out in the diagnosis of scabies by providing

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accurate, non-invasive, and effective methods. This study aims to develop a deep learning-based mobile application, named ScabAI, for the accurate detection of scabies from skin images. By leveraging Convolutional Neural Networks (CNN), the research seeks to enhance early detection, improve diagnostic accuracy, and provide a user-friendly mobile tool that can be accessed directly by users. ScabAI is designed to achieve high sensitivity, specificity, and overall classification accuracy, making it a reliable solution for preliminary scabies diagnosis. Additionally, this study aims to contribute to the broader adoption of artificial intelligence in dermatology by offering an accessible and efficient diagnostic application that addresses both clinical needs and user convenience.

2. MATERIALS AND METHODS (MATERYAL VE METOD)

2.1. Dataset and Preprocessing Used (Kullanılan Veri Seti ve Ön İşleme Süreci)

In this study, publicly available datasets containing images related to scabies were used. The collected images were labeled as scabies or non-scabies by experts. A non-scabies category was created using 250 images of other skin conditions and healthy skin, while the scabies category was formed using 250 images of skin affected by scabies.

The VGG Image Annotator (VIA), a platform-independent JavaScript application, was utilized for labeling the images and marking the regions of interest [19]. After the regions marked by experts were cropped, all images were resized to a resolution of 256x256 pixels to create the dataset used for the development of the deep learning model. An image from the obtained dataset is presented in Figure 1.

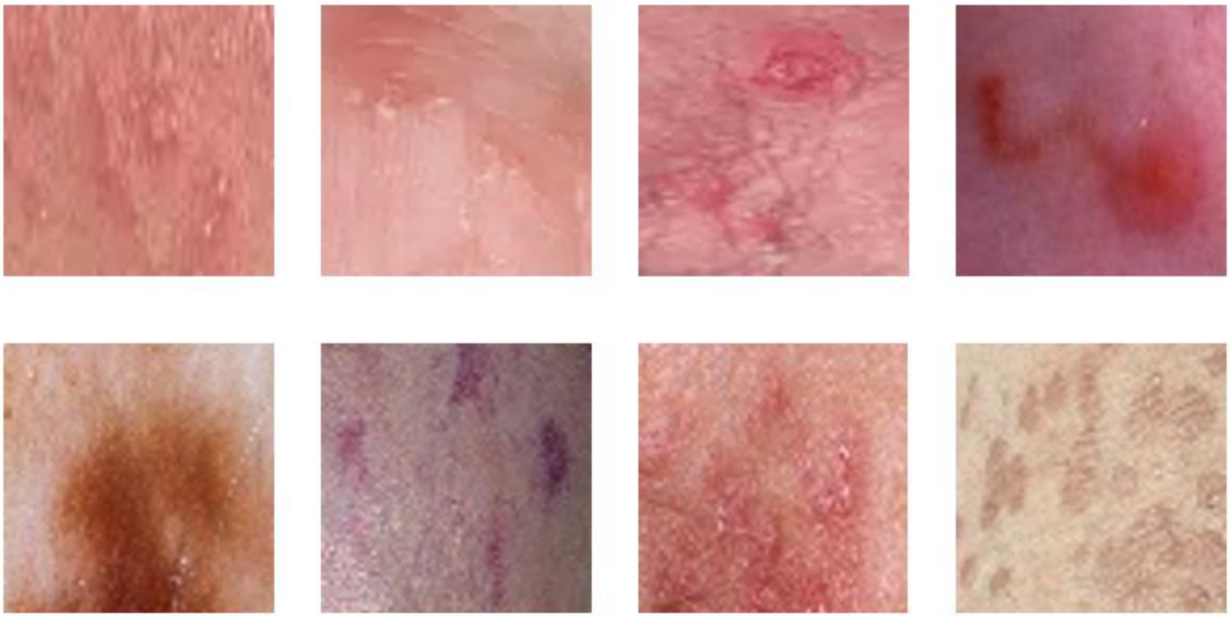

Figure 1. A preview of the dataset used (Kullanılan veri setinin önizlemesi)

2.2. Programming Environment (Programlama Ortamı)

The dataset was created, and preprocessing tasks on the images were carried out using a computer with an Intel i7 processor and 16 GB of RAM, alongside the Python programming language. During the training of the CNN model, the Keras module was used, and the training was conducted on a CPU. For developing the mobile application, the React Native framework was chosen.

2.3. Convolutional Neural Network (CNN) (Evrişimli Sinir Ağı)

Convolutional Neural Networks (CNNs) have emerged as a powerful architecture in the realm of deep learning, particularly excelling in tasks related to image processing and classification. The architecture of a CNN is typically composed of several distinct layers, each serving a specific function that contributes to the overall capability of the network. Understanding these layers is crucial for grasping how CNNs operate and their applications in various fields, including medical imaging, facial recognition, and object detection [20], [21].

The fundamental building block of a CNN is the "convolutional layer". This layer performs convolution operations on the input data using a set of learnable filters or kernels. Each filter is designed to detect specific features, such as edges or textures, by sliding across the input image and computing dot products. The convolutional layer significantly reduces the number of parameters in the model compared to fully connected layers, as the same filter is applied across different regions of the input, thus leveraging weight sharing [22], [23]. This characteristic not only enhances computational efficiency but also aids in capturing spatial hierarchies in the data. Convolution is shown in Equation 1 and Equation 2.

$$G[m,n] = (f * h)[m,n] \tag{1}$$

$$G[m,n] = \sum_j \sum_k h[j,k] f[m-j, n-k] \tag{2}$$

Following the convolutional layer, CNNs typically include a "pooling layer". Pooling serves to down-sample the feature maps generated by the convolutional layers, thereby reducing their dimensionality and computational load while retaining essential information. The most common types of pooling are max pooling and average pooling, which select the maximum or average value from a set of values in the feature map, respectively [22]. This operation helps to make the representation invariant to small translations in the input, which is particularly beneficial in tasks like image classification where the exact position of features may vary.

Batch normalization (BN) layer is another layer used in CNN. In deep learning architectures, each layer serves as the input for the subsequent layer. The learning process in one layer must be completed before the next layer begins its learning process. Normalization typically standardizes input values at the initial stage, but intermediate layers do not benefit from this early normalization. Consequently, issues such as slower training, instability, or gradient vanishing—where learning occurs at a minimal level—may arise. BN is implemented to mitigate these challenges and improve training efficiency and stability [20].

After several convolutional, pooling and, batch normalization layers, the architecture transitions into "fully connected layers". These layers are similar to traditional neural networks, where every neuron is connected to every neuron in the previous layer. The role of fully connected layers is to interpret the features extracted by the convolutional and pooling layers and to produce the final output, such as class probabilities in classification tasks [24].

In addition to these primary layers, CNNs may incorporate "non-linear activation functions" such as Rectified Linear Units (ReLU) (Equation 3) and sigmoid (Equation 4) after each convolutional layer. These functions introduce non-linearity into the model, allowing it to learn complex patterns in the data [24]. Furthermore, dropout layers are often employed to improve training stability and prevent overfitting, respectively [25].

$$ReLU(x) = \max(0, x) \tag{3}$$

$$sigmoid(x) = \frac{1}{1+exp^{-x}} \tag{4}$$

Recent advancements in CNN architectures have led to the development of more sophisticated layers and structures, such as depthwise separable convolutions and residual connections, which aim to enhance performance while maintaining efficiency [26]. These innovations demonstrate the versatility of CNNs and their adaptability to various tasks beyond image classification, including video processing and natural language processing [22], [26].

2.4. Metrics Used (Kullanılan Metrikler)

In the domain of machine learning, particularly for classification tasks, it is essential to assess model performance using a variety of metrics. These metrics offer valuable insights into the effectiveness of a model and facilitate the comparison of different models. Important performance indicators include accuracy, sensitivity (recall), specificity, F1 score and, confusion matrix.

The confusion matrix is a fundamental tool for analyzing the performance of a classification algorithm. It is a table that summarizes the model's performance by comparing its predicted classifications with the actual outcomes. The matrix comprises four elements:

- True Positives (TP): The number of instances accurately predicted as positive.
- True Negatives (TN): The number of instances accurately predicted as negative.
- False Positives (FP): The number of instances incorrectly predicted as positive (Type I error).
- False Negatives (FN): The number of instances incorrectly predicted as negative (Type II error) [27].

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Accuracy is the proportion of correctly predicted cases (including both true positives and true negatives) relative to the total number of instances, calculated as Equation 5.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Sensitivity, also referred to as recall, assesses the percentage of actual positive cases that are accurately detected. Sensitivity is especially critical in medical diagnostics, where failing to detect a positive instance (such as a disease) may lead to severe consequences. Specificity, on the other hand, measures the percentage of actual negative cases that are correctly identified. Specificity is vital in contexts where false positives can result in unnecessary treatments or stress [28]. Specificity and sensitivity are calculated according to Equation 6.

$$Sensitivity = \frac{TP}{TP+FN},\ Specificity = \frac{TN}{TN+FP} \quad (6)$$

The F1 score is the harmonic mean of precision and recall, offering a balanced metric between the two. It is particularly advantageous when working with imbalanced datasets. The F1 score ranges from 0 to 1, where a value of 1 indicates perfect precision and recall [27]. The formula for the F1 score is given at Equation 7.

$$\mathrm{F}_1 Score = \frac{2*TP}{2*TP+FP+FN} \quad (7)$$

3. EXPERIMENTAL STUDY AND RESULTS (DENEYSEL ÇALIŞMA VE BULGULAR)

3.1. Network Design and Hyperparameter Optimization (Ağ Tasarımı ve Hiperparametre Optimizasyonu)

The proper preparation of data and the selection of suitable hyperparameters for the model directly affect its success. Incorrect parameters can negatively impact the training of the model and the results obtained. In this study, many parameters have been optimized for creating the model. Determining the parameters that provide the most effective performance on the model is a time-consuming process. One of the most critical stages is selecting the appropriate number of neurons and layers for the model. Regarding the number of neurons used in the CNN architecture, filters with 4–8–32, 4–8–32–64, and 4–8–32–128 neurons were tested. For the Fully Connected layer, 4, 8, 16, and 32 neurons were experimented with. To determine the activation functions of the CNN design in the model, “ReLU,” “tanh,” “SELU,” “softsign,” “softmax,” and “sigmoid” functions were tested. Various optimization algorithms, such as “Adam,” “Nadam,” “SGD,” “RMSprop,” and Adamax, were employed to select the optimizer. To establish the appropriate dropout rate in the model, values of 0.2, 0.3, 0.4, 0.5, and 0.6 were tested. The batch size parameter was evaluated with values of 4, 8, 16, 32, and 64. The number of epochs, which indicates how many times the entire training data is shown to the created network, was tested with 100, 200, and 400 to determine the appropriate number of cycles. Testing all these parameters together would require approximately 27,000 trials, which would take considerable time. Therefore, some parameters were divided and tested separately to reduce the testing time and determine the suitable parameters.

In the CNN model created in this study, three convolution layers with 4, 8, and 32 neurons were utilized. The size of the filter matrix for the convolution layer was set to 3 × 3, with padding set to “same.” Maxpooling2D and a 2 × 2 kernel were used in the pooling layer. Batch Normalization was applied to all three layers. The activation function used in the intermediate layers was “ReLU,” while “sigmoid” was used in the output layer. The optimizer selected was “RMSprop,” and the epoch size was set to 200. The Fully Connected layer employed 4 neurons, and the batch size was determined to be 8. Additionally, a Dropout layer with a rate of 0.4 was incorporated to complete the model design. This model classifies the predicted results as “Scabies” and “Non-scabies.” The deep learning network created as part of the application is presented in Figure 2. In the dataset, 70% of the images (350) were used for training, while 30% (150) were utilized for validation.

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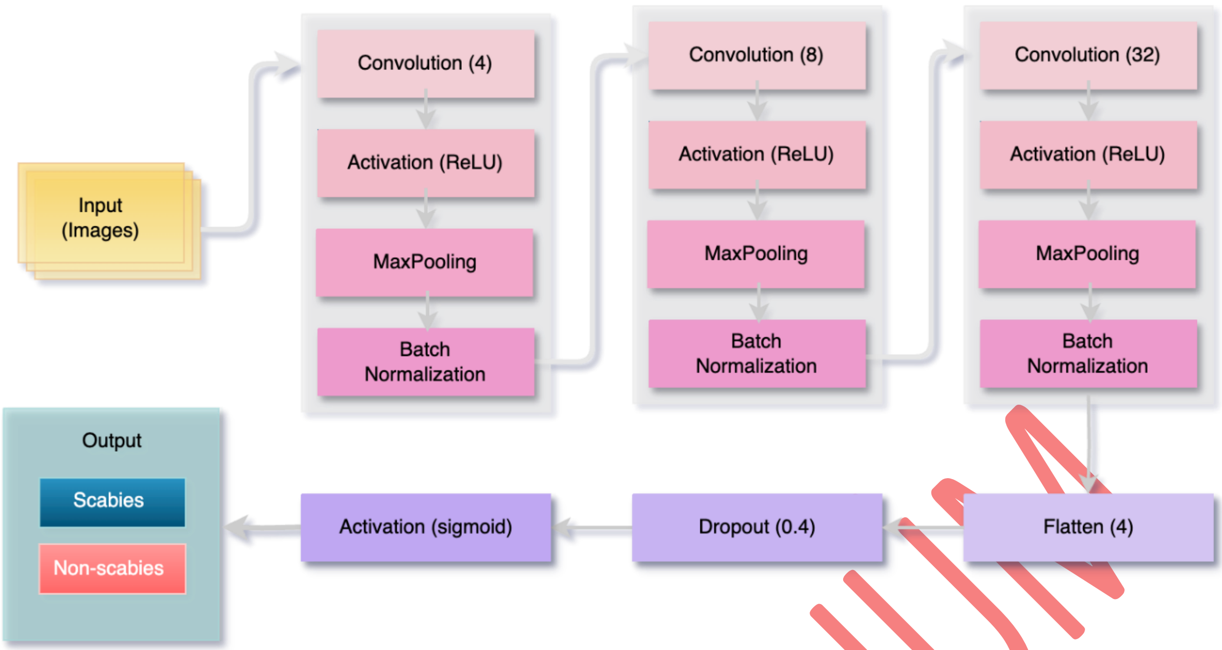

Figure 2. Design of deep learning model (Derin öğrenme modelinin tasarımı)

3.2. Training Information (Modelin Eğitim Bilgileri)

The current study utilizes a deep learning (DL) network to train skin images. The training process is carried out for a total of 200 epochs with a batch size of 8 for efficient data processing. At the start of training, the validation loss value is 0.76, and it gradually decreases to 0.019 by the end of the training. Similarly, the validation accuracy starts at 59% and reaches 96% by the end of the training (Figure 3). After saving the model's weights, the average time taken by the model to predict each sample is measured as 0.2 seconds.

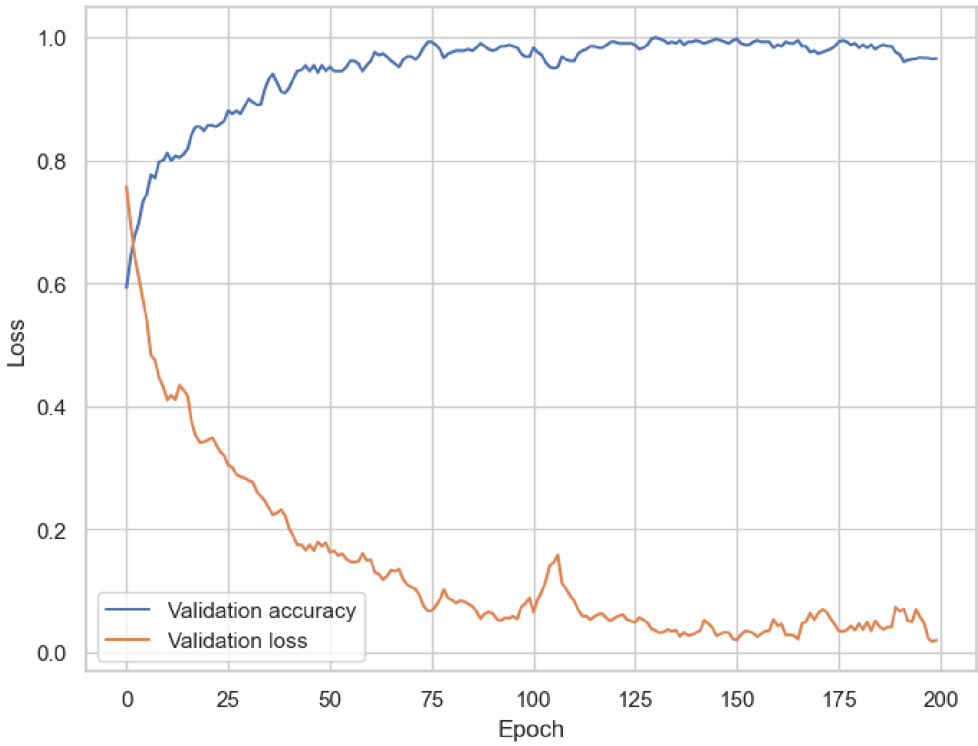

Figure 3. Graphic of validation values (Doğrulama verilerinin grafiği)

3.3. Evaluation of Training (Model Eğitimin Değerlendirilmesi)

In this study, a deep learning-based model was employed to detect scabies and non-scabies conditions from skin images, and the model's performance was evaluated using 150 images. Of these images, 75 belonged to individuals with scabies, while the other 75 were related to non-scabies skin conditions or healthy individuals. The model's success was analyzed using common performance metrics such as accuracy, sensitivity, specificity, and F1 score.

The results obtained indicate that the model operates with high accuracy. The accuracy rate of the model was found to be 96.7%. This value suggests that the model is generally successful in detecting scabies and has accurately classified a significant majority of the tested images.

The sensitivity metric was determined to be 96%. This rate indicates that the model has a high ability to correctly identify scabies cases, and the rate of false negatives is low. Such a high sensitivity suggests that the likelihood of missing scabies cases is minimal, indicating that the model is reliable for disease detection.

The specificity metric was obtained at 97.3%. This value reflects the model's rate of correctly identifying non-scabies conditions. The high specificity rate indicates that the model has a low false positive rate, thereby providing accurate classifications for non-scabies conditions as well.

The F1 score, which evaluates the balance between sensitivity and precision, was calculated at 96.5%. This high F1 score demonstrates that the model is balanced and effective in both detecting scabies cases (sensitivity) and making correct positive identifications (precision).

Overall, the deep learning model used in this study demonstrates successful performance in detecting scabies from skin images, evidenced by high accuracy, sensitivity, and specificity rates. The confusion matrix corresponding to the results is presented in Figure 4.

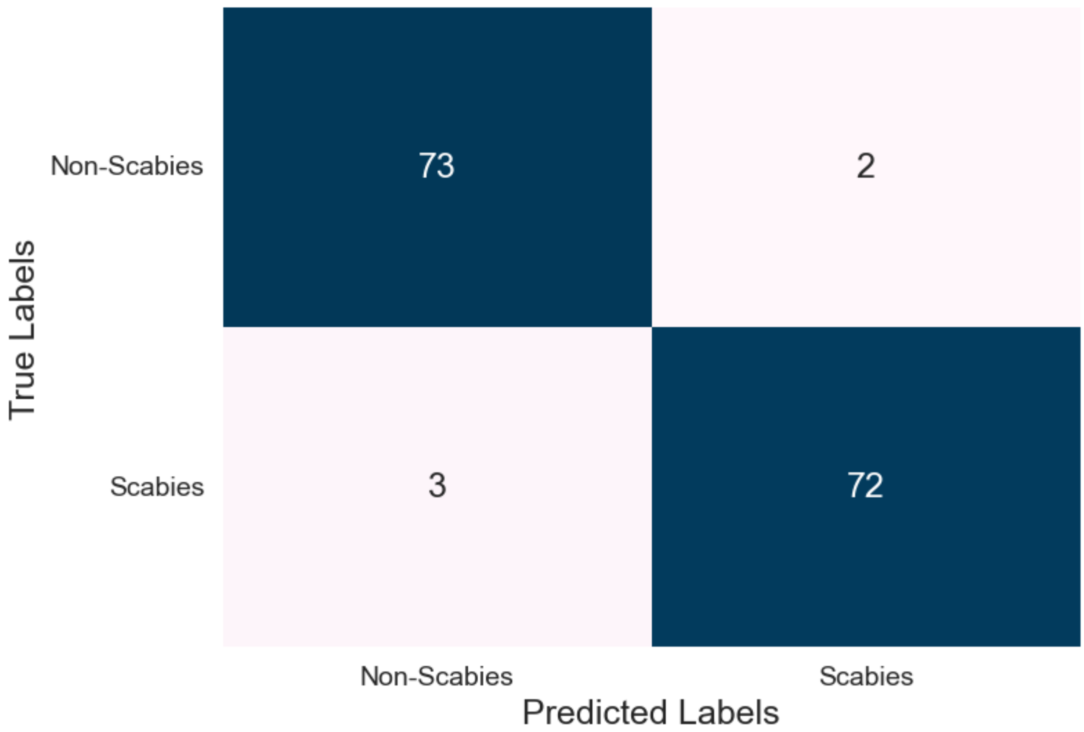

Figure 4. Confusion matrix of the results (Sonuçların karmaşıklık matrisi)

Within the scope of this study, the pre-trained models VGG16, VGG19, and ResNet-50 were trained and tested on the same dataset. However, their accuracy rates remained around 90%, with VGG16 achieving 86.0%, VGG19 achieving 88.0%, and ResNet-50 achieving 91.3%, respectively.

3.4. Developed Mobile Application (Geliştirilen Mobil Uygulama)

A mobile application called "ScabAI" has been developed using React Native for the detection of scabies disease on skin images. This mobile application features several functionalities, including the ability to capture images using the camera, upload existing images from the gallery, mark the relevant skin area on the uploaded images, predict based on the marked area using the trained model, and display the prediction on the screen.

The prediction process after marking the image is facilitated by a Python-based backend application that utilizes the model weights for accurate results. To enable users to take photos directly from the mobile application, necessary libraries have been integrated, and the required permissions for camera access have been defined. FastAPI has been used to enable communication between the application and the Python backend. The image is captured and annotated within the mobile application, then sent to the Python backend via FastAPI. The backend processes the image using a pre-trained model to make a prediction and transmits the prediction result back to the mobile application. This process allows the system to determine whether the image corresponds to scabies within an average of 3 seconds. Currently, these application permissions are functional on mobile devices running the Android operating system. Screenshots of the user interface for the developed application are presented in Figure 5.

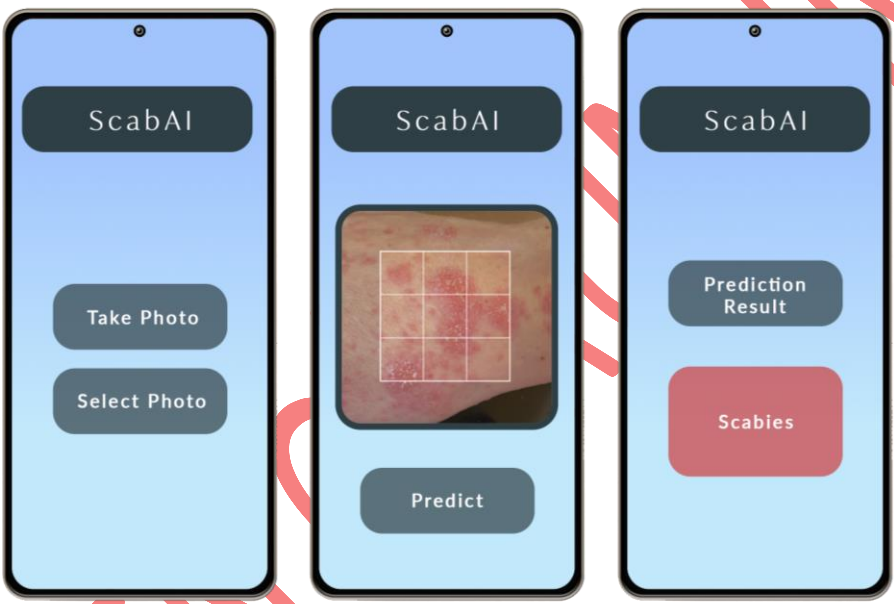

Figure 5. Screenshots of mobile application (Mobil uygulama ekran görüntüleri)

4. DISCUSSION (TARTIŞMA)

In this study, a CNN-based model for scabies detection, achieving an accuracy of 96.8%, with sensitivity, specificity, and F1-score values of 96.5%, 97.2%, and 96.5%, respectively is developed. Compared to other research in the field, our model demonstrates competitive performance, especially in terms of sensitivity and specificity, making it a reliable tool for accurate scabies diagnosis. The relevant studies are given in Table 1 along with their performance metrics.

Table 1. Relevant studies in the literature (Literatürdeki ilgili çalışmalar)

Paper	Dataset volume-Scabies	Used ML method	Metric results
Yasir et al. (2014)	277	Artificial Neural Network (ANN)	Accuracy: 89%
Parikh et al. (2015)	87	Artificial Neural Network (ANN), SVM	Accuracy: 97.17% for all diseases, no exact values for Scabies
Arifin et al. (2012)	182	Artificial Neural Network (ANN)	Accuracy: 98.67%
Sam et al. (2019)	65	Convolutional Neural Network (CNN)	Accuracy: 84.7%
Akmalia et al. (2019)	10	Local Binary Pattern (LBP), Convolutional	Accuracy: 90%

		Neural Network (CNN)	
Bajwa et al. (2020)	611	Deep Neural Networks (DNN)	Precision: 77.42% Sensitivity: 70.70% Specificity: 99.27% F1 Score: 73.91
Halder et al. (2022)	141	Convolutional Neural Network (CNN)	Accuracy: 97.25%
Our study	500	Convolutional Neural Network (CNN)	Accuracy: 96.7% Sensitivity: 96% Specificity: 97.3% F1 Score: 96.5%

The dataset volume used in this study (500 images) is larger than in several other studies, which often ranged from 10 to 277 images. This larger dataset likely contributed to the robustness and generalization of our model, as evidenced by the higher accuracy and balanced performance metrics. For instance, models using smaller datasets have reported accuracies ranging from 84.3% to 97.2%, suggesting that dataset size plays a crucial role in model performance, as larger datasets generally enhance learning and generalization, both of which are critical for reliable scabies detection.

Deep neural networks (DNNs) employed in other studies achieved an accuracy of 77.7%, with a sensitivity of 70.6%, specificity of 99.5%, and an F1 score of 73.9%. Although these models performed well in terms of specificity, they had lower sensitivity and overall accuracy compared to our CNN model. This indicates that DNNs can excel in distinguishing non-scabies cases but might be less effective in detecting positive scabies cases, underscoring the importance of achieving a balance between sensitivity and specificity for effective screening.

Moreover, studies that utilized artificial neural networks (ANNs) reported accuracy rates between 89.5% and 97.2%, but they generally had smaller datasets. This limitation may affect the models' ability to generalize effectively in diverse real-world scenarios. In contrast, our CNN model not only achieved high accuracy but also maintained balanced sensitivity and specificity, making it more suitable for clinical applications in detecting scabies.

Overall, the findings from this study highlight the significance of using a sufficiently large dataset and the effectiveness of CNNs in achieving both high accuracy and balanced classification metrics. This contributes to the growing body of evidence supporting CNNs as a reliable approach for scabies detection, with potential implications for broader dermatological applications. Although our study has achieved higher accuracy compared to most studies in the literature, different datasets have been used in these studies. Therefore, using the same datasets may lead to different results. It is recommended that such preliminary diagnosis applications be tested with various datasets.

Moreover, unlike many similar studies in the literature, this study not only focused on developing a model but also aimed to create a machine learning-based mobile application that allows users to easily conduct inquiries by taking photos or selecting images from their gallery. This approach goes beyond merely developing an academic model, offering a practical solution that users can benefit from in their daily lives. The developed application aims to detect scabies at an early stage, thereby improving the quality of life for individuals. In this regard, the study not only enhances diagnostic accuracy but also provides a user-friendly solution that contributes to the early detection of the disease.

5. CONCLUSIONS (SONUÇLAR)

This study introduced ScabAI, a deep learning-based mobile application designed to detect scabies from skin images, utilizing Convolutional Neural Networks (CNNs) to achieve high diagnostic performance. The model achieved a notable accuracy of 96.7%, with a sensitivity of 96%, specificity of 97.3%, and an F1 score of 96.5%. These results indicate that the model not only accurately identifies scabies cases but also minimizes false positives and negatives, making it a highly effective tool for initial scabies detection. The large dataset of 500 images, which included 250 scabies cases and 250 non-scabies cases, played a critical role in enhancing the model's robustness, supporting better generalization and reliability. This larger dataset size represents an improvement over previous studies, which generally used smaller datasets, often resulting in lower generalization capabilities. By leveraging a more comprehensive

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dataset, ScabAI demonstrates superior performance metrics and the potential to reliably detect scabies across diverse real-world scenarios.

The practical significance of this study extends beyond the development of an accurate model, focusing also on creating a mobile-based solution that is user-friendly and accessible to the broader population. ScabAI allows users to either upload an existing image or capture a new image of a suspected scabies rash directly through the mobile app. The application then processes the image using a Python-based backend, employing the CNN model to provide rapid and accurate predictions. This functionality makes ScabAI a useful tool for both healthcare providers and individuals, supporting early scabies detection, timely treatment, and ultimately reducing the potential for outbreaks and severe complications associated with delayed diagnosis. The mobile application's emphasis on speed, convenience, and accuracy aligns with the growing demand for AI-powered tools in healthcare that offer real-time support for decision-making and patient care.

The findings of this study highlight the importance of data quality, model optimization, and user-centric design in developing AI-based medical applications. While ScabAI demonstrates significant promise, future research could focus on several areas for further enhancement. Expanding the dataset with more diverse images, including different stages and skin types, could improve model accuracy and generalization. Incorporating additional machine learning techniques, such as ensemble methods or hybrid models, may further refine performance, especially in distinguishing between scabies and other skin conditions with similar presentations. Another area for future exploration is the integration of multilingual support and broader functionality in ScabAI, making it more accessible across different regions and user demographics.

In conclusion, ScabAI not only represents a significant advancement in AI-assisted dermatological diagnostics but also serves as a practical solution to a global public health issue. By offering a reliable, rapid, and user-friendly approach to scabies detection, this mobile application has the potential to improve the quality of life for individuals affected by scabies. Furthermore, this study exemplifies how AI can be harnessed to address neglected diseases, contributing to better healthcare outcomes, reducing the burden on healthcare systems, and fostering a more proactive approach to disease management and control. As artificial intelligence continues to evolve, ScabAI sets a precedent for the development of similar tools targeting other dermatological conditions, demonstrating the transformative impact of AI-driven healthcare solutions.

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DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

***Hakan YILMAZ*:** He supervised the study, contributed to the writing of the manuscript, and was responsible for the model design and implementation.

***Zeynep Nida CAN*:** She conducted the literature review and contributed to the data collection process.

***Hatice Şevval BAKİ*:** She conducted the literature review and contributed to the data collection process.

***Tahsin ÇÖKMEZ*:** He conducted the literature review and contributed to the data collection process.

***Mehmet ÖZDEM*:** He proofread the manuscript and contributed to the interpretation of the results.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

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